Analysis of Labor Markets and Migration: The Role of Education, Skills and Tasks

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Dekan:	Prof. Dr. Michael Roos
Referent:	Prof. Dr. Thomas K. Bauer
Korreferent:	Prof. Dr. Christoph M. Schmidt
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1 Introduction

1.1 Overview

Do immigrants steal our jobs? Do robots take over our jobs? These two questions have been part of public concerns in many industrialized countries. These concerns were accelerated by the recent immigrant inflows and the rapid technological advancements, and were rooted in discussions in the media in the last years. Demographic change, globalization and new technologies alter the nature of labor markets and pose various challenges, but also provide opportunities to the labor force.

Two major trends over the last decades have drastically shaped the labor markets with respect to skill requirements of jobs and the respective returns to skills in the industrialized world. First, average years of schooling has been increasing steadily around the world. The share of people with tertiary education is substantially higher compared to some decades ago. Second, skill requirements of jobs have been changing due to the automation of routine tasks as a result of the advancements in computer technology. Automation and digitization at the workplace have radically altered the definitions of occupations, their skill requirements, and also returns to skills. These changes prompted a debate on higher risk of job insecurity and growing inequality. Furthermore, recent discussions of the technological change emphasize the growing importance of skills and workplace tasks, in addition to formal education, to understand the ongoing changes in the labor markets.

Beyond digitization, aging populations challenge many industrialized countries in matching the labor and skill demand of the labor markets. Skill deficits arising from technological development and digitization necessitate an inflow of high-skilled labor, which can be met by immigration of high-skilled workers. For economies to benefit effectively from migration, immigrants need to be allocated into occupations which correspond to skill level. However, overeducation arises as a common phenomenon among immigrants in many countries. Analyzing the labor market outcomes of immigrants is important for understanding the mechanisms that facilitate or hinder the integration of immigrants and for conducting more successful migration policies which correspond to the needs of labor markets.

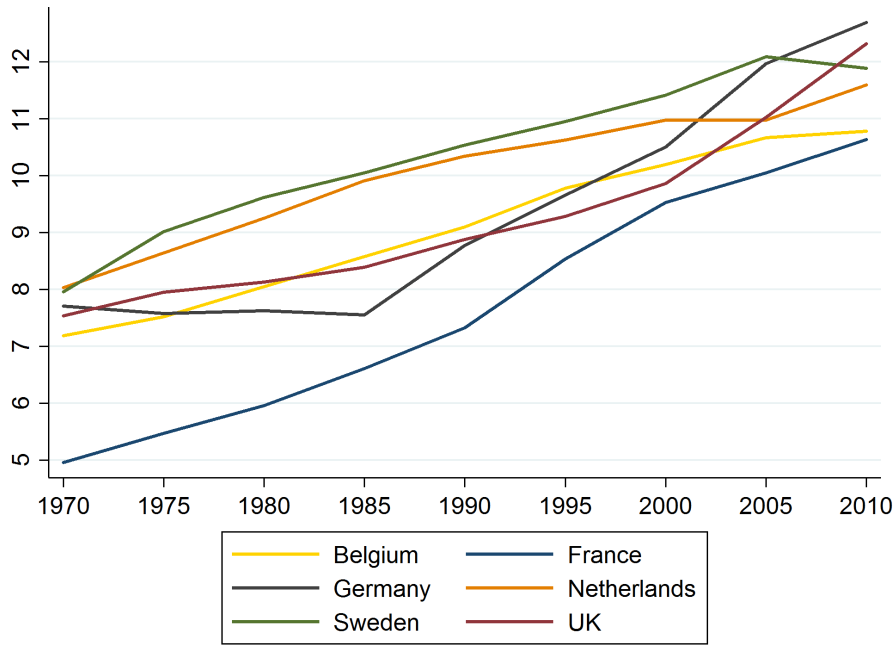
Against this background, this dissertation analyzes the recent trends in the labor markets as well as immigrant-native discrepancies with respect to educational and occupational outcomes. **Chapter 2** focuses on the educational differences between natives and immigrants and investigates the prevalence of qualification-occupation mismatches among immigrants compared to natives in Europe. **Chapter 3** studies the impact of automation on the labor market transitions of workers in Germany. Finally, **Chapter 4** examines how immigration influences the occupational attainment of natives by considering the role of workplace tasks.

1.2 Labor Market Trends and Migration

The supply of high-skilled workers has been steadily increasing over the last decades in almost all countries. Figure 1.1 depicts the sharp increasing trend in the average years of schooling in some European countries. The expansion of educational attainment coincides with the increased adoption of computer-based technologies. This phenomenon is called as skill-biased technological change (SBTC), which claims that both the years of schooling and the returns to education increased via a faster growth in the skill demand than in the skill supply (Acemoglu, 2002; Katz & Autor, 1999).

Labor markets experienced a rapid increase in the diffusion of computerization. SBTC hypothesis suggests that computers substitute low-skilled workers and complement high-skilled workers. However, a more recent strand of literature state that replacement of labor by computers is not monotonically related to the skill level, but rather to the task content

Figure 1.1: Average Years of Schooling

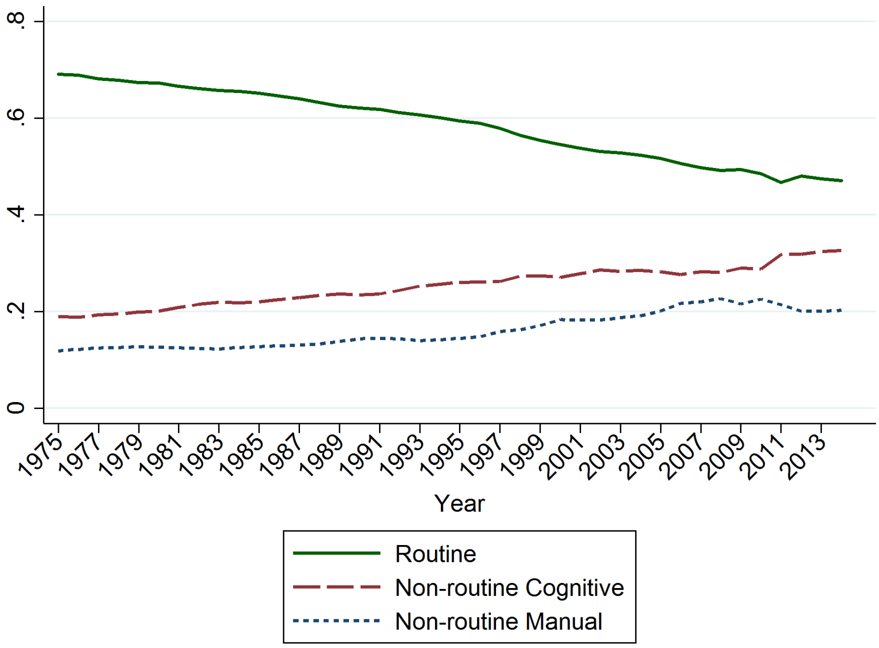


Source: World Bank statistics based on Barro-Lee data, own calculation.

of the jobs (Autor, Levy, & Murnane, 2003). The approach employed in this literature is called as "task-based approach", in which skill demands are measured by the activities workers perform in their jobs instead of the skill level of workers. Acemoglu and Autor (2011) define tasks as a unit of work activity that produces output, i.e., goods and services, whereas skills refer to a worker's endowment of capabilities for performing various tasks. Distinguishing between skills and tasks is especially relevant when workers with the same skill level perform a variety of tasks and respond differently to technological change with respect to the set of tasks they perform. Acemoglu and Autor (2011) emphasize the necessity of building a framework that considers the allocation of skills to tasks to better evaluate the impact of technological change on the labor market.

The idea behind the task-based approach is that routine tasks are easily programmable. Therefore, occupations which are intense in routine tasks are most prone to automation. Figure 1.2 shows the pattern of employment in 3 task categories, i.e., routine, non-routine cognitive and non-routine manual, over the last decades in Germany. The share of employment in routine occupations has been steadily decreasing since the 1970s.

Figure 1.2: Pattern of Employment Growth by Task Groups in Germany



Source: SIAB 1975-2014, own calculation.

The exposure to automation is not linearly related to the skill level. Not all low-skilled jobs are routine in nature, i.e., waiters perform mostly non-routine manual tasks and they are less affected by computerization, whereas clerks have higher education levels but are affected by computerization to a larger extent. Therefore, the SBTC hypothesis is replaced by a nuanced version called as routine-biased technological change (RBTC).

As routine tasks are more heavily represented in middle-skilled occupations, routinization led to a dramatic decrease in middle-skilled employment during the last decades. At the same time, employment in high-skilled and low-skilled occupations, though to a lesser extent in the latter, increased. This evidence of employment polarization has been detected in many industrialized countries, e.g., Germany (Spitz-Oener, 2006), the UK (Goos & Manning, 2007), the EU (Goos, Manning, & Salomons, 2009) and the US (Cortes, 2016) . Routinization increased the job insecurity of middle-skilled workers. On the other hand, the evidence on the relation between employment polarization and wage inequality differs between countries. Autor, Katz, and Kearney (2008) argue that employment polarization led to an increase in the wage inequality in the US, whereas Antonczyk, Leuschner, and Fitzenberger (2009) and Antonczyk, DeLeire, and Fitzenberger (2010) show no such evidence for Germany.

While the routine content of jobs determines the scope of labor replacement by computers, the overall impact of changing workplace tasks on the labor market is more extensive. Jobs mainly require a broad set of tasks which cannot only be classified by their routine or non-routine nature. For example, Spitz-Oener (2006) states that the complexity of tasks has significantly increased since the 1970s in Germany. The shares of analytical and interactive tasks increased, whereas occupations experienced a shift away from routine cognitive and manual tasks.

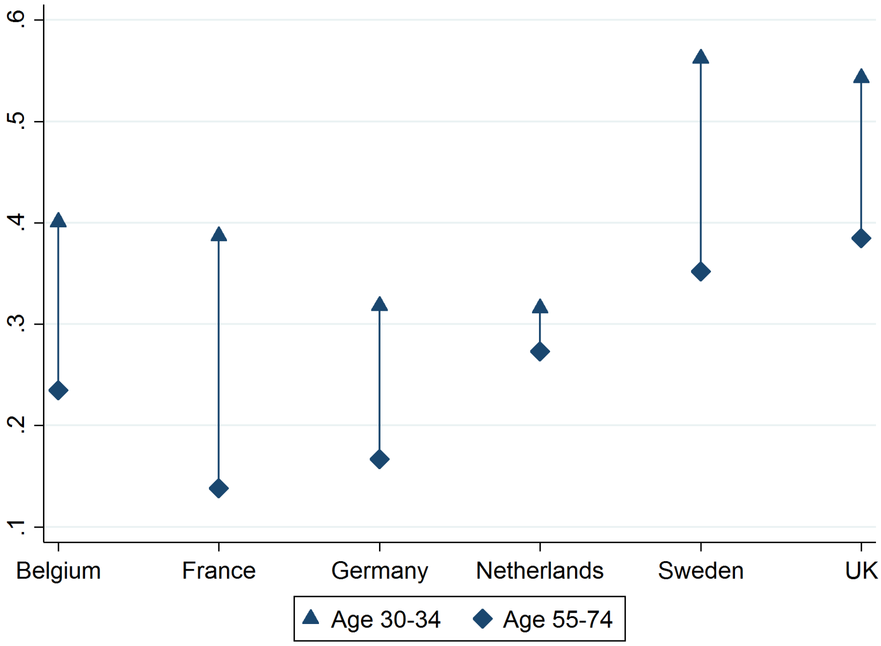
As technological advancements and changing workplace requirements necessitate a sufficient supply of high-skilled labor, a deficit of skilled workers emerges. Despite the educational upgrading in the industrialized world, aging populations impede meeting skill needs of labor markets. Therefore, immigration should be promoted to cope with the skill shortages.[1]

The skill profile of immigrants has changed substantially over the last decades. Figure 1.3 displays the share of immigrants with tertiary education for different cohorts, i.e., those aged 30 to 34, and 55 to 74. Former immigrant cohorts, who mainly represent the guest worker generation in Europe, are being replaced by more skilled younger cohorts in the labor market. Educational expansion of immigrants seems promising for the immigrant-receiving economies to meet their skill needs.

Matching immigrants with occupations which correspond to their skill levels yet remains a challenge. The well-known example of foreign scientists working as taxi-drivers in host countries suggest that the inflow of high-skilled immigrants is not always effective for economies to cover their skill shortages. This phenomenon of holding a higher level of formal educa-

[1] See the annual report of German Council of Economic Experts (2017) for a discussion on digitization and immigration.

Figure 1.3: Share of Immigrants with Tertiary Education



Source: Eurostat, own calculation.

tion than job requirements is referred to as overeducation and is commonly considered as a brain waste. Overeducation is more prevalent among immigrants compared to natives in many major developed countries (Nieto, Matano, & Ramos, 2015). One of the main reasons behind this finding is the imperfect international transferability of human capital, which explains a major part of the native-immigrant gaps in labor market outcomes (Basilio, Bauer, & Kramer, 2017).

The quality of education in the origin country is also an important determinant of the education-occupation match that immigrants experience in host countries. Examining the quality of learning outcomes of students in many countries, the OECD Programme for International Student Assessment (PISA) reveals substantial differences in the educational performance of students between countries (OECD, 2016). PISA results are commonly interpreted as a proxy for the quality of educational systems around the world. Thus, the differences in the performance of students are likely to represent the quality differences between countries.

Moreover, Bauer (2002) shows that overeducation reflects the heterogeneity of abilities and skills within educational qualifications. Accounting for the individual heterogeneities becomes especially relevant when we study the overeducation of immigrants. Immigrants differ from their native counterparts with respect to both observable and unobservable individual characteristics. Against this background, it is not clear whether overeducation among immigrants implies a genuine mismatch or represents the incomparability of skills and formal qualifications between natives and immigrants.

1.3 Contributions

Chapter 2 (co-authored by Michael Kind and Jan Kleibrink) analyzes the prevalence of overeducation among immigrants in 11 European countries and discusses whether overeducation can be interpreted as genuine overqualification. Differences in the quality of education between countries make it difficult to compare the scope of overeducation of immigrants to that of natives. Thus, an accurate comparison requires looking beyond the internationally incomparable educational degrees and accounting for more comparable measures of skills.

Exploiting a recent study by OECD, the Programme for the International Assessment of Adult Competencies (PIAAC) provides the framework to account for individual heterogeneities in skills. In addition to a rich set of socioeconomic characteristics, the PIAAC study employs internationally comparable cognitive skill tests which allows us to use the individual cognitive scores as a proxy for unobserved ability. We apply a probit analysis on the prevalence of overeducation and find that immigrants are more likely to be overeducated than their native counterparts. However, the same pattern is not observed in terms of cognitive overskilling. We define genuine overqualification as the state of being both formally overeducated and cognitively overskilled and find that the likelihood of being genuinely overqualified is much lower among immigrants than natives. Our results suggest that formal education is a weak proxy for the qualification of immigrants and formal overeducation cannot be interpreted as genuine overqualification.

Moreover, a significant heterogeneity among immigrants with respect to their origin, length of residence in the host country and native language is observed. Immigrants from Western countries and immigrants speaking the same native language as in the host country are more similar to natives in their overqualification patterns. Formal overeducation is more prevalent among recent immigrants. Immigrants who have been resident of the host country for more than ten years become more similar to natives in terms of both formal overeducation and genuine overqualification. Overall, our results emphasize the importance of taking into account different measures of skills as well as the country where the formal education was acquired when analyzing the education-occupation match of immigrants.

Chapter 3 (co-authored by Ronald Bachmann and Colin Green) analyzes the patterns of labor market polarization as a result of automation of routine tasks in Germany. Although there is a large body of literature on the effect of polarization at an aggregate level, little is known about the individual level adjustments in the labor market. We fill this gap in the literature by providing evidence on the short- and long-run adjustment process at individual level exploiting the administrative data set Sample of Integrated Labor Market Biographies (SIAB). We utilize unique labor surveys conducted by BIBB (Federal Institute for Vocational Education and Training), IAB (Institute for Employment Research), and BAuA (Federal Institute for Occupational Safety and Health) to measure the task content of occupations based on the reported workplace activities of workers. The repeated BIBB/BAuA/IAB surveys allow us to capture the changing task requirements of occupations for a long time period.

We demonstrate a marked shift in employment away from occupations involving a high share of routine tasks. We also show that exposure to high routine task content is associated with reduced likelihood of being in employment in both short (one year) and medium term (five years). The employment penalty to routineness of work has increased over the last four decades. Routine task content is associated with reduced job stability and higher likelihood of experiencing periods of unemployment. However, the negative effects of routine work appear to be concentrated in increased employment-to-employment and employment-to-unemployment transitions rather than longer periods of unemployment.

Finally, **Chapter 4** focuses on the heterogeneity between natives and immigrants in regard to their workplace tasks. Due to the differences in their skill endowments, immigrants and natives perform different jobs and tasks. The degree of substitution between natives and immigrants to perform certain tasks is a major determinant of the labor market effect of immigration on the native population. Until recently, the literature analyzing the labor market implications of immigration on local labor markets considered the substitutability in regard to education level. Incorporating the task-based approach in this context allows to account for skill differences within the same education level and to analyze the role of workplace tasks as a factor of immigrant-native substitution.

Against this background, Chapter 4 analyzes whether natives specialize in communication intense tasks as a response to immigration in Germany by exploiting the SIAB and BIBB/BAuA/IAB data as in Chapter 3. Due to their language proficiency, natives have a comparative advantage in performing jobs that require communication skills. Therefore, specializing in communication tasks can mitigate potential negative effects of immigration on natives. This adjustment mechanism can potentially explain why the literature finds no adverse employment and income effect of immigration on the natives in Germany.

The chapter contributes to the literature by providing evidence for Germany on the task specialization hypothesis. Additionally, it incorporates the role of changing task requirements of occupations over time. More specifically, the paper examines the source of task response of natives, i.e., whether immigration reallocates natives into more communicative occupations or whether natives are represented more frequently in those jobs that experienced a higher increase in communication tasks over time.

The results show that natives in Germany respond to immigration by increasing their supply of communication tasks and decreasing supply of manual tasks. Disentangling the change in the overall task supply of natives shows that a major part of the change in the task supply arises from changing workplace requirements within occupations. Only a small part of the change is caused by natives' occupational mobility. Moreover, these results are driven by younger workers and the middle-skilled workers while older and the low-skilled workers do not show a significant response.

1.4 Policy Implications

Automation and digitization are substantially changing the labor market structure. While some jobs are being automated, certain skills are gaining more importance in the labor market. Routine tasks are being replaced by computers, whereas analytic/cognitive and interactive/communicative tasks are becoming more valuable. As computers are shown to be complementary to high-skilled labor and substitute to middle-skilled workers, there is an increasing employment polarization.

While technological change requires sufficient high-skilled labor, a sustainable supply of high-skilled workers is a challenge in societies with aging population. High-skilled immigration, however, can cover skill shortages. For economies to benefit more efficiently from immigration, immigrants need to experience occupational matches which correspond to their skill levels. Chapter 2 shows that overeducation rates are quite high in many main immigrant-receiving countries and points at the importance of the country where the education is obtained. Only promoting the inflow of high-skilled immigrants without further consideration on their occupational attainment may not ensure that migration contributes to meet the skill shortages. Therefore, immigration policies should attract younger individuals who could attain (further) education or training in the host countries.

Contrary to the findings of Frey and Osborne (2017), who claim that about 50% of occupations will be automated, Arntz, Gregory, and Zierahn (2016) suggest that occupations are being partly automated but not completely replaced by computerization. Although technological change does not entirely destruct jobs or hollow out the wage distribution, it certainly implies challenges to certain groups in the labor market by steadily changing the skill requirements of the jobs. Chapter 3 provides evidence that workers in routine intensive occupations experience unemployment more frequently. Thus, workers performing routine tasks are more prone to automation and face a higher job insecurity. Technological change is apparently an ongoing process and workplace tasks are getting more complex over time. Coping with the changing workplace requirements necessitates continuous acquisition of new skills. This is especially relevant for middle-skilled workers, as the decreasing employment in middle-skilled occupations pushes them either upward or downward on the occupational hierarchy. Therefore, life-long-learning gains an important role to cope with technological change.

The task content of occupations provides important insights to relate the skills of workers to their occupational attainment. In the context of explaining labor market discrepancies between immigrants and natives, the focus has been mainly on the formal education until recently. Chapter 4 shows that differences in skill endowments cause natives and immigrants with similar education level to perform different tasks and not to compete for the same jobs. Therefore, the public concerns about immigrants stealing jobs from natives are not supported by these findings.

While performing different tasks mitigates adverse labor market effects of immigration on natives, it implies difficulties for immigrants to integrate into the labor market and catch up with natives in the era of digitization. Since tasks are gaining more importance relative to formal education, immigrants should invest more in acquiring skills, which are becoming more valuable such as communication skills, to catch up with natives. Training programs as a tool of integration policies can facilitate the skill acquisition for immigrants and closing the gaps with their native counterparts with respect to labor market outcomes. Providing education and training in the fields which are gaining more importance would also benefit receiving countries to directly cover the shortages in targeted skills.

2 Occupational Mismatch of Immigrants in Europe: The Role of Education and Cognitive Skills*

Abstract. Occupational mismatch is a wide-spread phenomenon among immigrants in many European countries. Mismatch, predominantly measured in terms of education, is often regarded as a waste of human capital. Such discussions, however, ignore the imperfect comparability of international educational degrees when comparing immigrants to natives. An accurate analysis of occupational mismatch requires looking beyond internationally incomparable educational degrees and considering more comparable skill measures. Using PIAAC data, it is possible to exploit internationally-comparable cognitive skill measures to analyze the presence of mismatch disparities between immigrants and natives. This allows us to examine whether overeducation implies only an apparent phenomenon or rather a genuine overqualification observed also in the form of cognitive overskilling. In this study, we analyze differences in the incidence of being overeducated and being cognitively overskilled between immigrants and natives in 11 European countries. Results show that immigrants are more likely to be overeducated than natives, while the opposite is true for being cognitively overskilled. Furthermore, significant heterogeneity among immigrants in the incidence of overeducation and cognitive overskilling can be detected.

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*This paper is co-authored by Michael Kind and Jan Kleibrink and is available as Ruhr Economic Paper #687.

2.1 Introduction

Migration is often stated to be a promising remedy to counteract demographic change in industrialized countries. Technological change and rapid aging have led many European countries to implement more liberal policies to attract high-qualified immigrants not only at national but also at EU level, such as the blue card.[1] The economic success of such migration-oriented strategies depends –among other factors– on the quality of occupational matches of immigrants in the receiving labor markets.

Up to now, the mismatch literature mainly focused on *overeducation* of immigrants, describing a state of holding higher formal education than necessary to perform their jobs. Specifically, previous research has found that immigrants are more frequently overeducated than natives in many developed countries – for example C. Green, Kler, and Leeves (2007) in Australia, Joona, Gupta, and Wadensjö (2014) in Sweden, and Sanroma, Ramos, and Simón (2008) in Spain. Overeducation is widely considered as not fully utilizing the available human capital. Thus, governments are asked for policy interventions, such as regulating the recognition of educational degrees from abroad or implementing skill-based entry criteria to improve job match quality of immigrants for a more efficient utilization of human capital. However, these discussions generally disregard the international incomparability of educational systems. Educational degrees of immigrants obtained in their home countries are only imperfectly comparable to the degrees of natives obtained in the host countries. Thus, the sole focus of the mismatch discussions on educational degrees, e.g., years of education, might be shortsighted.

Compared to formal skills, cognitive skills are less prone to incomparability between countries. Cognitive skills, such as numeracy and literacy skills, can be measured on country-independent scales and thus allow for more suitable comparisons between natives and immigrants. Following Hanushek and Woessmann (2012), cognitive and formal skills are seen as components of overall qualification. Thus, considering only one dimension cannot answer the question whether someone is genuinely overqualified. In this paper, we distinguish between three definitions of occupational mismatch: formal overeducation, cognitive overskilling and

[1] For a detailed review of migration policies in Europe, see Kahanec and Zimmermann (2011) and annual report of the Expert Council of German Foundations on Integration and Migration (2015).

genuine overqualification. We first study the prevalence of *formal overeducation*, i.e., holding more formal education than required for the job, among immigrants. Additionally, we analyze whether immigrants are more likely than natives to be *cognitively overskilled*, i.e., whether immigrants have on average more cognitive skills than needed to perform their jobs. Lastly, we examine whether immigrants are more likely to be *genuinely overqualified*, i.e., whether among those who are formally overeducated, immigrants are also more likely to be cognitively overskilled than natives.[2]

The main contribution of this paper is its new approach to analyze occupational mismatch by taking both perspectives – cognitive skills and formal education – into consideration. In contrast to the dominant view in the empirical literature, we claim that overeducation does not per se imply overqualification, unless an individual is cognitively overskilled at the same time. The OECD data of the Programme for the International Assessment of Adult Competencies (PIAAC), a dataset mainly designed to assess labor market related skills, allow us to use comprehensive cognitive skill measures on a representative, international level to analyze differences between immigrants and natives. Furthermore, using a rich set of information on individual characteristics, our paper offers a detailed subgroup analysis of immigrants based on their ethnic background and the length of residency in the host country.

Our results show that immigrants are more likely than natives to be formally overeducated but not cognitively overskilled. Therefore, the interpretation of excess education as a waste of human capital, so-called brain waste, is shortsighted. International incomparability of educational degrees requires considering more comparable measures, such as cognitive skills to assess the occupational mismatch of immigrants. Focusing on genuine overqualification (the state of being overeducated and cognitively overskilled at the same time) shows that in numerous European labor markets, immigrants do not suffer from unused human capital compared to their native counterparts. Our analysis further shows that countries of origin and the length of stay are important determinants of occupational mismatch among immigrants.

[2]Throughout this paper, we sometimes use shortly overeducation instead of formal overeducation and overskilling instead of cognitive overskilling. It should, however, be kept in mind that in our definition overeducation only refers to excess formal education and overskilling refers to excess cognitive skills. The terms overqualification and genuine overqualification are also used interchangeably.

The paper is structured as follows: Section 2.2 provides an overview of the literature on the definitions of mismatch and the earlier empirical findings. Section 2.3 introduces the data source of our empirical analysis. The empirical strategy as well as results are presented in section 2.4. Section 2.5 presents concluding remarks.

2.2 Overeducation and Overskilling

The vast majority of the occupational mismatch literature has considered overeducation – defined as having more formal education than required for a job – as an indicator for a waste of human capital. Empirical evidence shows that immigrants are more likely to be subject to overeducation than natives (Nieto et al., 2015). Various explanations for the higher incidence of overeducation among immigrants exist. Some studies claim that immigrants compensate the lack of country-specific human capital with excess education (C. Green et al., 2007; Kler, 2005). Others argue that at arrival, immigrants have a lack of knowledge in local labor markets, which results in inadequate job-matches (Piracha, Tani, & Vadean, 2012). However, these short-term frictions are expected to disappear over time as immigrants gain more experience in the host country labor market. Finally, not all educational degrees obtained abroad are officially recognized by the host countries, e.g., the *Meister* degree/licence in Germany, or by employers due to quality differences in education in different countries.

While overeducation has received considerable attention in empirical labor economics, there is no consensus on how to measure it. Three common methods are applied in the literature. The first one is based on workers' self-assessment of skill requirements of their jobs (Frei & Sousa-Poza, 2012; Pecoraro, 2014; Sicherman, 1991; Sloane, Battu, & Seaman, 1999). This method has been argued to be a suitable measure of educational matches because the evaluation of jobs comes directly from those individuals performing the jobs. However, the main strength of this method has also been shown to be its biggest weakness. Subjective evaluations can be subject to different sources of problems. For instance, the benchmark of the answers is unclear (Bauer, 2002). While some respondents might consider the education necessary to get a job as a benchmark, others might rather evaluate their experience concerning day-to-day tasks. Furthermore, individual educational attainment will most likely serve as orientation and therefore influence answers.

The second method is based on experts' job analyses. In this method, job analysts define educational requirements for each occupation. Commonly used classifications are the Dictionary of Occupational Titles (DOT) in the US (McGoldrick & Robst, 1996; Rumberger, 1987) or the Standard Occupation Classification of Statistics Netherlands (Baert, Cockx, & Verhaest, 2013). Individuals with more years of schooling than required are defined as overeducated. One major shortcoming of this approach is that such classifications do not exist for many countries. On the other hand, although an evaluation by labor market experts can provide precise information on the necessary education for most jobs, it has to be updated regularly. Otherwise it can lead to an increasing prevalence of measurement errors over time (Kiker, Santos, & de Oliveira, 1997).

The third method uses realized job matches (RM) as a measure of educational mismatch (Bauer, 2002; Kiker et al., 1997; Nielsen, 2011; Verdugo & Verdugo, 1989; Voon & Miller, 2005). In the RM approach, the individual educational attainment is compared to the mean education within an occupation. Some studies use the average years of education in each occupation and add one standard deviation to determine the threshold of being overeducated (e.g., Bauer, 2002; Verdugo & Verdugo, 1989), while others use the mode years of schooling as the educational requirement (e.g., Bauer, 2002; Chiswick & Miller, 2009; Kiker et al., 1997; Kleibrink, 2013; Mendes de Oliveira, Santos, & Kiker, 2000; Ng, 2001). The RM method can be automatically updated with every wave of a panel dataset and relying on realized matches is not prone to subjective misspecifications.

Following Bauer (2002); Kiker et al. (1997); Nielsen (2011); Verdugo and Verdugo (1989); Voon and Miller (2005), the RM method is applied in this study by using average years of education within an occupation as a benchmark. While educational mismatch can appear in the form of over- as well as undereducation, the focus of the literature – and the following empirical analysis – lies on overeducation as this is far more prevalent. Furthermore, in contrast to overeducation, undereducation is not regarded as a problem per se.

While a comparison of the formal education attained in different countries is relatively simple – either by comparing the years spent in education or educational titles – the set of abilities that is connected to an educational title can vary considerably between educational systems (e.g., Kahn, 2004; Pellizzari & Fichen, 2013). International studies, like the Programme for International Student Assessment (PISA) by the OECD, compare cognitive skills of students in the same age groups around the world. Results show that the test scores of 15-year-old students in several subjects, e.g., science, reading, mathematics, vary substantially across countries. As a result, overeducation of immigrants can be a result of imperfect international comparability of educational degrees rather than simply implying a waste of human capital. Moreover, immigrants might engage in overeducation as a strategy to compensate for a lack of country-specific knowledge or abilities. Previous analyses (e.g., Bauer, 2002; F. Green, McIntosh, & Vignoles, 1999; Korpi & Tåhlin, 2009; Poot & Stillman, 2010) argue that human capital compensation is a driving force behind overeducation. Here, individuals compensate for their lack of innate abilities with extra years of schooling. Therefore, individuals appear to be overqualified in terms of education but this does not necessarily imply overqualification in terms of ability. Hence, overeducation does not per se correspond to genuine overqualification and cannot always be regarded as brain waste.

In order to overcome the shortcoming of imperfect comparability of educational degrees between immigrants and natives, this study explores differences in cognitive skills. Here, the question arises on how to measure cognitive skills. Some studies use proxy variables for skills. Sohn (2010), for example, uses school grades in mathematics as a proxy for cognitive skills. However, comparing the success within educational systems still suffers from quality differences between educational systems. Alternatively, the subjective method of self-assessment can be used to determine the skill-occupation match. Individuals respond to survey questions on the utilization of their skills at work (Allen & van der Velden, 2001). This approach, however, suffers from the same problems as the subjective approach for measuring overeducation mentioned above. One of the most commonly applied methods is to use scores from ability tests (Allen, Levels, & van der Velden, 2013), such as the IALS (Kahn, 2004) or the PIAAC (Hanushek, Schwerdt, Wiederhold, & Woessmann, 2015). These tests are specifically designed to assess the cognitive skills of individuals and are preferred by many authors on the grounds of objectivity. Against the background of this discussion, we utilize individual-level cognitive skill tests from the PIAAC as a proxy for the unobserved abilities of individuals.

2.3 Data

We employ cross-sectional survey data from the Programme for the International Assessment of Adult Competencies (PIAAC) conducted by the OECD in 24 countries[3] between 2011 and 2012. Approximately 166,000 individuals aged 16 to 65 answered the survey. Each participating country is represented by around 5,000 individuals.[4]

The strength of the PIAAC data is the information provided on internationally comparable measures of cognitive skills. Individuals engage in tests aiming at assessing their cognitive abilities in three domains – literacy, numeracy and problem-solving in technology-rich environments. The tests are computer-based and conducted in the official language of the participating countries.[5] The test on problem-solving in technology-rich environments is only answered by those who declare previous computer experience. The core test lasts approximately 60 minutes where individuals answer 20 questions in each skill domain from a large pool of sample questions. The scores of the tests are reported on a scale of 0-500 for each skill domain.[6]

We restrict our sample to a smaller subset of countries due to two reasons. First, immigrants are significantly underrepresented in some countries and the immigrant sample size is not sufficient to conduct a meaningful analysis.[7] Second, the information on some key variables essential for our analysis is not available or coarsened in some countries.[8] This leaves us with a final sample of 11 European countries (Belgium, Denmark, France, Germany,

[3]Australia, Austria, Belgium (Flanders), Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), and the United States.

[4]An exception in terms of sample size is Canada with around 26,000 observations.

[5]Individuals without computer skills take a paper-and-pencil test. Some countries apply the test in multiple languages which are widely spoken within the country.

[6]For a detailed description of obtaining the skill measures, see OECD (2013). The data provide ten plausible values for the cognitive skill scores. We use the first plausible value reported as suggested by Allen et al. (2013) and Hanushek et al. (2015).Reapplying the analyses using other plausible values/the mean of ten plausible values does not change our results.

[7]Japan, Korea, Poland, Slovak Republic.

[8]Austria, Canada, Estonia and Finland due to occupational information and the US due to region of birth information.

Ireland, Italy, Netherlands, Norway, Spain, Sweden, UK).[9] We further restrict our sample to employed individuals, i.e., part-time or full-time employed, excluding the unemployed, students, interns and compulsory military servants. Finally, our sample of immigrants consists of first-generation immigrants only, who migrated after finishing their education in the home country. As second-generation immigrants attend school fully in the host country, they are not subject to imperfect international transferability of education. Therefore, they are excluded from our sample in the main analyses and are examined separately. Our final sample of natives and first-generation immigrants consists of 37,259 individuals and additionally 1,335 second-generation immigrants.

In a first step, we reproduce the results from the existing literature by examining the likelihood of formal overeducation. Applying the realized match (RM) method, the binary overeducation variable takes the value one if a person is formally overeducated and zero otherwise. We calculate mean years of education within each occupation using the two-digit ISCO classification[10] in each country.[11] We add one standard deviation to the average years of education in order to determine the threshold for being overeducated. Those who are above the threshold are defined as overeducated.

Among the three skill domains in the dataset, we use numeracy and literacy skills separately as measures of cognitive ability.[12] We assume that numeracy scores measure the skill dimension which is least dependent on language proficiency. The validity of the results is examined using also literacy scores. A pretest of the survey allows us to identify and sort out those individuals who do not possess any host country language skills. Thus, our final sample includes only individuals with at least a minimum level of language proficiency.

[9] We further excluded Cyprus and Czech Republic as they differ from the other countries in our sample with respect to their migration history. We additionally exclude Russian Federation as the data are claimed to be preliminary. Due to coarsened information on many variables in the public-use-file of Germany, we use the scientific-use-file obtained from GESIS and merge it to public-use-files of the other countries.

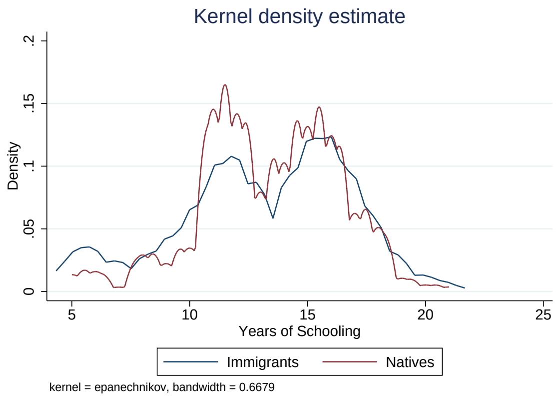
[10] A three-digit ISCO classification is available for a subset of countries and it leads to very small cell sizes when estimating the mean education separately in each country. Estimation results using the three-digit ISCO classification in the pooled sample are in line with the results using the two-digit ISCO classification in each country. Results are available on request.

[11] Occupation cells with less than 20 observations are excluded. Applying median or mode instead of mean results in similar incidence of overeducation. However, we stick to the mean in order to have a comparable overeducation measure with the overskilling measure which is calculated from a continuous cognitive skill measure on a scale of 0 to 500. The large range of cognitive skill measure hinders using the alternative methods for overskilling.

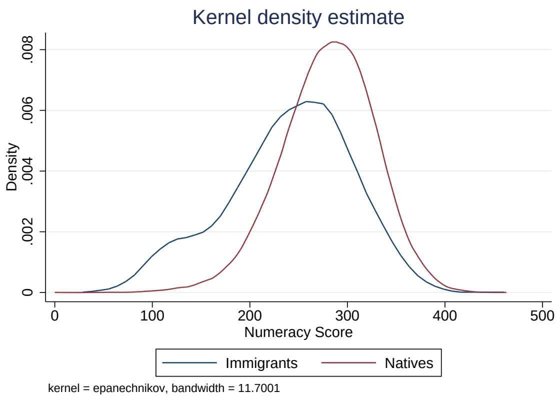
[12] Problem-solving in technology-rich environment domains is not applied in all countries. Therefore, we exclude this test from our analysis.

In order to compare the likelihoods of cognitive overskilling and formal overeducation, we construct the skill mismatch variable in the same way as the overeducation variable, i.e., adding one standard deviation to the mean value of cognitive skill scores calculated in each occupation based on the two-digit ISCO classification in each country. Following the same reasoning, our overskilling variable takes the value one if an individual is cognitively overskilled and zero if not.

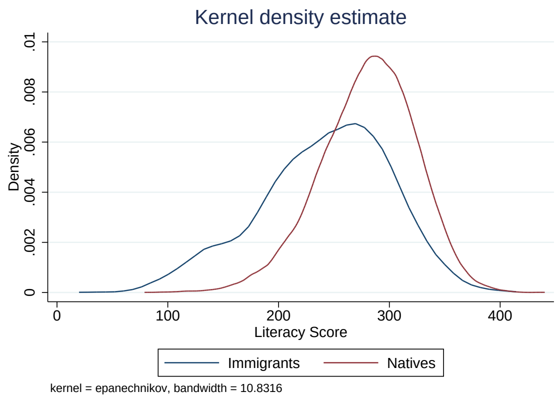
Figure 2.1: Kernel Density Estimate of Education and Skill Measures



(a) Years of Schooling



(b) Numeracy Score



(c) Literacy Score

Note: Authors' calculations based on the PIAAC.

Figure 2.1 displays the kernel density estimates of years of education and the two skill measures for natives and immigrants. The first panel shows that natives and immigrants are very similar in their educational attainment. The average years of schooling of natives (13.4) and immigrants (13.1) are almost identical. However, such a pattern is not observed in the skill measures. Immigrants have a more left-skewed distribution compared to natives in both numeracy and literacy skills. The average of the skill scores of immigrants (240) is approximately 40 points lower than it is for natives (280) in both skill domains, which is a statistically significant difference.

In line with previous findings, the incidence of overeducation is much higher for immigrants, i.e., compared to 25% of the immigrants only 13% of the natives are formally overeducated. On the contrary, the share of cognitively overskilled immigrants (7-9%) is lower than the share of overskilled natives (15%) in both literacy and numeracy domains. While shares of formally overeducated and cognitively overskilled natives are very close, the difference is substantial for immigrants, suggesting that education and cognitive skills are not equivalent indicators of overall qualification.[13]

In the following regression analysis, we control for commonly used covariates in the overeducation literature (age, sex, marital status, having children, health status, full/part-time employment, public/private sector).[14] Our main variable of interest is the migration status. We define immigrants as those individuals, who obtained their whole education in the home country, excluding those who attained their education partly in their host country. Immigrants who arrived before the age of five and immigrants born in the host country are grouped as 'second-generation immigrants' and are analyzed separately. Migration status is defined as a dummy variable, taking the value one for immigrants and zero for natives.

2.4 Empirical Strategy and Results

Our main analysis is based on separate logit estimations on being overeducated, overskilled and overqualified at the individual level using the pooled sample of 11 countries. Each estimation accounts for the individual control variables mentioned in the previous section as well as country fixed effects.

[13] The shares of overeducated and overskilled individuals in each country are presented in Table A2.11 in the appendix.

[14] See A2.1 in the appendix for the definition of control variables and Table A2.2 for the descriptive statistics.

We start with a binomial logit model on being overeducated in order to examine whether immigrants are more likely to be overeducated than natives. We proceed with an analysis of the probability of being cognitively overskilled in a second step. If formal education and cognitive skills measured the same dimension of mismatch, similar coefficients on migration status in both models would be expected. Positive coefficients in both models, i.e., being more likely to be overeducated and overskilled, would suggest that immigrants are more likely to suffer from brain waste than natives, while opposite signs of the coefficients would suggest that heterogeneity between educational systems is an important factor of occupational mismatch of immigrants.

The logit estimations allow us to conclude whether immigrants are more likely to be formally overeducated or cognitively overskilled compared to natives. However, they do not answer the question whether immigrants are more likely to suffer from genuine overqualification – being overeducated and cognitively overskilled at the same time. As previously discussed, it has been argued that immigrants who suffer from overeducation are subject to a waste of human capital. Economies could benefit from the unused human resources by ensuring appropriate occupational matches of immigrants. We question this conclusion and extend the previous literature by examining whether among those who are classified as overeducated, immigrants are also more likely to be cognitively overskilled. Thus, we estimate a logit model on being cognitively overskilled conditional of being overeducated and examine whether overeducation of immigrants is a reliable indicator of genuine overqualification.

In a final step, we split our binary measure of cognitive skill mismatch into three categories, i.e., overskilled, matched and underskilled, to estimate multinomial logit models among the group of formally overeducated individuals. The binary measure of cognitive skill mismatch classifies the groups of underskilled and correctly matched individuals in one group. The separation into three categories allows us to examine genuine overqualification in more depth. More specifically, we can examine whether overeducation is a result of human capital compensation. This means that overeducated individuals possess excess schooling as a compensation for the lack of cognitive skills, which can be observed as underskilling in our classification. Those who are overeducated and correctly matched in cognitive skills are worse off than the former group and this might be considered as a form of mismatch, however, they are not subject to overqualification by our definition.

2.4.1 Occupational Mismatch of Immigrants

The first column of Table 2.1 shows the results from logit estimations on overeducation. Our results confirm previous findings by showing that immigrants are about 7% more likely to be overeducated than natives.

Table 2.1: Logit on Overeducation and Overskilling by Migration Status

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Immigrant	0.074***	-0.085***	-0.154***	-0.119***	-0.191***
	(0.008)	(0.014)	(0.031)	(0.014)	(0.034)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

Columns (2) and (4) of Table 2.1 reveal that immigrants are about 9-12% less likely to be cognitively overskilled than natives. Thus, occupational mismatch appears to be a less severe problem for immigrants than natives when cognitive skills are considered. A potential explanation for this finding is the screening process of employers. The assessment of educational degrees from abroad is difficult for employers as it requires elaborate knowledge on educational systems of other countries. Therefore, employers may screen the skills of immigrant employees to a larger extent in order to observe their true level of productivity. As cognitive skills of immigrants are monitored more carefully, they become less likely to be placed in jobs for which they are cognitively overskilled.

So far the results show the likelihood of occupational mismatches in terms of education and cognitive skills, separately. However, they do not yet indicate whether immigrants are more likely to suffer from genuine overqualification than natives. Therefore, we examine the likelihood of genuine overqualification (columns (3) and (5) of Table 2.1), which indicates the likelihood of being overskilled among the group of overeducated. Overeducated immigrants are 15-19% less likely to be cognitively overskilled than their native counterparts. This finding stresses that immigrants are significantly less likely to suffer from genuine overqualification than natives. Similar to cognitive overskilling, lower likelihood of genuine overqualification among immigrants might be a result of the screening of employers. Even though the higher incidence of overeducation among immigrants represents an apparent problem, it cannot necessarily be interpreted as a genuine overqualification, i.e., a waste of unused human capital.

In order to examine whether there are differences across countries, we also apply the same analyses on formal overeducation, cognitive overskilling and genuine overqualification separately in each country (see Table A2.12 in the appendix). Overall, country-specific regressions give qualitatively similar results in most countries to those obtained from the pooled sample. With the exception of Spain, immigrants in all countries covered in our sample are more likely to be overeducated than natives. Italy, which has experienced a recent and rapid increase in its immigrant population, displays the highest probability of formal overeducation among immigrants (17%). While immigrants are not significantly different than natives in Spain in their probability of being formally overeducated, they are less likely to be cognitively overskilled. However, this does not correspond to a genuine overqualification at the same time. Spain and Ireland appear to be the only countries where immigrants do not significantly differ from their native counterparts in terms of genuine overqualification, whereas in Ireland, they have a higher probability of being formally overeducated.

Table 2.2: Multinomial Logit on Skill Match Conditional on Being Overeducated

	Numeracy Skills			Literacy Skills		
	Underskilled	Matched	Overskilled	Underskilled	Matched	Overskilled
	(1)	(2)	(3)	(4)	(5)	(6)
Immigrant	0.085^{***}	0.057^{*}	-0.142^{***}	0.121^{***}	0.051	-0.172^{***}
	(0.013)	(0.032)	(0.031)	(0.013)	(0.034)	(0.033)
N	5,127	5,127	5,127	5,127	5,127	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

The main focus of our analyses has been on formal overeducation and cognitive overskilling. In a further step, we consider also cognitive underskilling as a separate outcome in a multinomial logit model, which allows us to examine the human capital compensation hypothesis by showing whether a formally overeducated individual possesses lower cognitive skills than required by his job. Table 2.2 shows the results on the cognitive skill match (in numeracy as well as literacy skills) conditional on being overeducated. Among the overeducated, immigrants have a higher probability of being cognitively underskilled and correctly matched compared to natives. This finding provides evidence supporting the human capital compensation hypothesis by showing that overeducated immigrants are more likely to be underskilled, meaning that immigrants compensate for a lack of skills caused by differences in educational systems by more years of schooling. Thus, their overeducation can neither be regarded as genuine overqualification nor as brain waste. Furthermore, the previously identified lower likelihood of immigrants to suffer from genuine overqualification can also be found applying a multinomial logit model – irrespective of the skill domain applied.

Empirical evidence shows that overeducation is more widespread among younger workers and its prevalence decreases by experience (Alba-Ramirez, 1993). Altonji and Pierret (2001) argue that employers discriminate against young workers as they put more emphasis on easily observed characteristics, such as formal education, as a measure of productivity. In order to examine whether the differences between immigrants and natives shown by our earlier results can be attributed to age differentials, we divide our sample into four age groups and estimate the occupational mismatch of immigrants in each group (see Table A2.7 in the appendix). Formal overeducation seems to be a problem for the elderly immigrants while the younger group of immigrants between the ages of 16 and 25 do not differ from their native counterparts. On the contrary, the elderly group of those over 55 years appear to be similar to natives in terms of cognitive overskilling and genuine overqualification while a significant difference to natives in formal overeducation prevalence remains.

We further examine formal overeducation and cognitive overskilling of immigrants in two different education groups, i.e., holding a university degree or more vs. a lower degree (see Table A2.8 in the appendix). When we restrict the sample only to high-educated individuals, the likelihood of being overeducated reaches up to 20% while the overskilling and overqualification profiles remain similar to the results from the overall sample. The results indicate that overeducation is a more relevant problem for high-educated individuals.

Finally, we divide the sample into occupational skill groups (see Table A2.10 in the appendix).[15] Formal overeducation seems to be less common in the skilled occupations while it is remarkably high in the semi-skilled white collar and elementary occupations. Another interesting finding is that only for those immigrants holding skilled occupations, cognitive overskilling and overqualification in numeracy and literacy domains appear to be similar. This is contrary to the common finding that the difference between natives and immigrants in cognitive overskilling is higher in literacy than in numeracy. Skilled occupations are characterized by strong communication as well as high-level numeracy and literacy skill requirements. In line with the skill requirements, immigrants in this skill level category have higher cognitive skill scores and the difference with natives is lower than in other skill categories. This explains why the difference in the probability of being cognitively overskilled in literacy is low between immigrants and natives in skilled occupations.

2.4.2 Years since Migration

Immigrants acquire local labor market knowledge and obtain host country-specific labor market skills by the length of stay. Thus, an assimilation in the likelihood of occupational mismatches appears to be likely. Therefore, we split the immigrant sample into three categories based on their lengths of stay. Table 2.3 reports heterogeneous effects for different lengths of residence in the host country. The longer a migrant lived in the host country, the less pronounced are the differences to natives in terms of occupational matches.

Immigrants who arrived within the last five years are 14% more likely than natives to be subject to overeducation. This effect appears to become smaller with the length of stay. Those immigrants who have been living in the host country for more than ten years are only 5% more likely to be overeducated than natives. While there is no clear and notable pattern of decrease in the probability of being cognitively overskilled, we observe a remarkable

[15] We use four ISCO skill level categories mapped to 1-digit ISCO occupational classification (See Table A2.9 for the definition of skill categories).

Table 2.3: Logit on Overeducation and Overskilling by Years Since Migration

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Years Since Migration:					
0-5	0.139***	-0.074***	-0.172***	-0.097***	-0.197***
	(0.026)	(0.015)	(0.034)	(0.012)	(0.031)
6-10	0.090***	-0.089***	-0.179***	-0.096***	-0.190***
	(0.021)	(0.012)	(0.034)	(0.012)	(0.034)
>10	0.052***	-0.054***	-0.064*	-0.075***	-0.075**
	(0.014)	(0.014)	(0.039)	(0.011)	(0.038)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regression weighted by sampling weights. Reference category is natives. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Full table including the control variables is presented in the Appendix.

decrease in the probability of genuine overqualification for those who have been residing in the host country for longer than ten years.

The assimilation pattern of immigrants might reflect two features. First, the focus of the screening of employers might be on education for more recent immigrants making them remarkably more likely to be formally overeducated. For immigrants residing in the host country for a longer time other characteristics, such as the labor market experience obtained in the host country, might play a more important role. Besides, immigrants might increase their skill level in the host country and acquire country-specific skills, which make them more similar to their native counterparts in their occupational match. Finally, the results might also reflect cohort differences. However, we cannot test this hypothesis due to the cross-section nature of our data.

2.4.3 Ethnic Origin

Previous studies (e.g., Nieto et al., 2015; Piracha et al., 2012) found that immigrants coming from culturally similar countries are less likely to be overeducated. Against this background, we split the immigrant sample into subgroups based on their ethnic background (see Table 2.4). According to the first column, all immigrant subgroups are 9-13% more likely to be overeducated than natives except the immigrants from North America & Western Europe. Employers do not fully recognize the educational degrees of immigrants who come from culturally distinct countries while those from North America & Western Europe, which are more similar to the host countries in our sample, are not significantly different from their native counterparts in terms of formal overeducation. However, a different pattern emerges when we examine cognitive skills. All immigrant subgroups regardless of their ethnic background are less likely to be cognitively overskilled than natives.

Table 2.4: Logit on Overeducation and Overskilling by Immigrant Ethnic Origin

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Born in:					
Arab States	0.096***	-0.084***	-0.091*	-0.111***	-0.171***
& Sub-Saharan Africa	(0.025)	(0.014)	(0.048)	(0.011)	(0.039)
Asia	0.107***	-0.081***	-0.200***	-0.120***	-0.229***
& the Pacific	(0.031)	(0.022)	(0.041)	(0.015)	(0.044)
Latin America	0.087***	-0.063***	-0.136**	-0.049**	-0.096
& the Caribbean	(0.031)	(0.022)	(0.064)	(0.023)	(0.067)
Central	0.126***	-0.061***	-0.141***	-0.097***	-0.181***
& Eastern Europe	(0.022)	(0.018)	(0.038)	(0.013)	(0.034)
North America	-0.001	-0.060***	-0.073	-0.045**	-0.020
& Western Europe	(0.017)	(0.018)	(0.056)	(0.019)	(0.059)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Reference category is natives. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Reference category is natives. Full table including the control variables is presented in the Appendix.

When we condition on being formally overeducated, all immigrants seem to be less likely to be cognitively overskilled (columns (3) and (5) in Table 2.4), except the group of North American & Western European immigrants.[16] For those immigrants, genuine overqualification is just as likely as it is for natives. This finding may arise from a lower effort invested by employers in the screening of North American & Western European immigrants due

[16]Immigrants from Latin America & the Caribbean are not significantly different from natives only in literacy overqualification.

to their cultural proximity. As a result, culturally dissimilar immigrants experience more appropriate job placements with a lower likelihood of a waste of human capital.

Table 2.5: Logit on Overeducation and Overskilling by Native Language

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Non-native Speaker	0.096***	-0.078***	-0.159***	-0.103***	-0.189***
	(0.013)	(0.010)	(0.024)	(0.007)	(0.021)
Native Speaker	0.063**	-0.037*	-0.010	-0.031	-0.015
	(0.026)	(0.021)	(0.067)	(0.021)	(0.073)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country. Reference category is natives.

Language skills are a substantial determinant of occupational success of immigrants. Therefore, we divide the immigrants into two groups based on the language they speak. Table 2.5 shows the differences between the immigrants whose native language is the same as the language spoken in the host country (native speakers) and those immigrants speaking a different language (non-native speakers). While native speakers still have a higher probability than natives to be formally overeducated, this probability is smaller compared to non-native speaker immigrants. While this result might be attributed to the differences in the language skills, this could also reflect the similarities in the educational systems of the host and home countries –where the same native language is spoken– due to colonial relations. Contrary to formal overeducation, native speaker immigrants appear not to be different from natives in the prevalence of overskilling and overqualification. However, non-native speaker immigrants are about 8-10% less likely than natives to be cognitively overskilled and 16-19% less likely to be genuinely overqualified.

2.4.4 Second Generation Immigrants

In our previous analysis, we excluded second generation immigrants. As second generation immigrants attend school fully in the host country, they are not subject to imperfect international transferability of human capital. Previous empirical findings show that education obtained in the host country is significantly more valued than the human capital acquired abroad (Friedberg, 2000; Nielsen, 2011). This makes second generation immigrants less prone to overeducation compared to their parents. They are additionally expected to possess better language skills than their parents and to be similar to their native counterparts. However, the ethnic discrimination hypotheses at the heart of overeducation discussions suggest that second generation immigrants would experience worse occupational matches than natives. Therefore, studying the second generation immigrants is important especially to examine the discrimination hypothesis.

Table 2.6: Logit on Overeducation and Overskilling of Second Generation Immigrants

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
	(1)	(2)	(3)	(4)	(5)
Second Generation Imm.	-0.005	-0.073***	-0.031	-0.085***	-0.050
	(0.011)	(0.014)	(0.042)	(0.014)	(0.041)
N	38,594	38,594	5,039	38,594	5,039

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column represents results from separate logit regression weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table 2.6 shows the results for the second generation immigrants. Natives and second generation immigrants do not show a statistically significant difference in their prevalence of being formally overeducated. While second generation immigrants are less likely to be cognitively overskilled than natives in both numeracy and literacy, they show no difference in their overqualification probability compared to natives. These results suggest that the observed formal overeducation among first generation immigrants does not imply an ethnic discrimination and may arise from the screening process of employers. Similarities between the second generation and the natives provide evidence against the ethnic discrimination and supports the previous findings that employers value the education obtained in the host country more highly.

2.5 Conclusion

Using PIAAC data for 11 European countries, this paper analyzes differences in the prevalence of occupational mismatch between immigrants and natives. Previous literature has stressed that overeducation appears to be a severe problem among immigrants. As a result, overeducation of immigrants is argued to imply foregone human capital for an economy. However, due to the international incomparability of educational degrees, this conclusion might be misleading.

By using test scores of computerized numeracy and literacy tests, we introduce cognitive skills as a measure of occupational mismatch which is not subject to the imperfect international comparability as formal education. We extend previous research by examining the occurrence of genuine overqualification among immigrants and analyze the likelihood of being cognitively overskilled conditional on being overeducated.

Concerning overeducation, our results are in line with previous studies. Formal overeducation appears to be much more common among immigrants than among natives. Estimates show that immigrants are about 7% more likely to suffer from overeducation than natives. However, results are remarkably different when analyzing cognitive skills. It is shown that immigrants are about 9% less likely to be cognitively overskilled and about 15% less likely to be genuinely overqualified than natives. Thus, the overeducation of immigrants does not imply an inefficient use of human capital as the higher incidence of overeducation does not correspond to a similar degree of genuine overqualification compared to natives.

Furthermore, our results highlight the importance of taking the heterogeneity among immigrants into account when assessing their occupational attainments. We show that the likelihood of overeducation, cognitive overskilling and genuine overqualification vary by the length of stay in the host country. An assimilation in the likelihood of being genuinely overqualified suggests that a potential waste of human capital seems to be mainly a problem of recent immigrants. By the length of residence in the host country, immigrants become more similar to natives in their probability of being genuinely overqualified. In addition, ethnic origin of immigrants appears to be of high importance. Immigrants from culturally similar regions, i.e., North America & Western Europe, do not significantly differ from their native counterparts in terms of overeducation and genuine overqualification, whereas other immigrants groups appear to be more likely to be overeducated but less likely to be overqualified. Therefore, considering the origin of immigrants is important when talking about human capital.

Our results suggest that labor markets work more appropriately than considered when it comes to the screening of immigrants. Employers seem to be aware of the international incomparability of educational degrees – as seen by the higher overeducation probability of immigrants – and invest more effort into the screening of immigrants. This is observed by a lower probability of immigrants in terms of overskilling and overqualification. As a higher incidence of formal overeducation does not correspond to an equivalent level of cognitive overskilling and as it is also shown by the overqualification analysis, we cannot talk about a prevalent waste of human capital among immigrants.

The results of this study are of descriptive nature. We neither show labor market outcomes of realized matches in the labor markets, nor can we make any statements concerning migration policies. However, we can show that the focus on educational degrees when examining occupational mismatches of immigrants appears to be shortsighted. Quality differences between educational systems have been extensively studied in economic and education research and have long been subject to political and societal debates. Not considering these factors when analyzing differences between natives and migrants in matching processes in the labor market is shortsighted and misleading. Our results for 11 European countries suggest that unused human capital – commonly referred to as brain waste – is a considerable issue in many countries. However, this cannot solely be seen as a problem of migration policies and must be treated as a general labor market problem concerning not only immigrants but also natives. Using cognitive skills as a proxy for the set of skills of individuals shows that the matching process in the labor market appears to be more adequate than suggested by studies with a pure focus on formal education.

A2 Appendix

Table A2.1: Definition of Control Variables

Variable	
Gender:	Dummy; 1 if the person is female
Age:	Continuous age; 16-65
Married:	Dummy; 1 if the person is married
Have Child:	Dummy; 1 if the person has at least one child
Health:	Self-assessed health status; 1(Excellent)-5(Poor)
Part time:	Dummy; 1 the person has a part-time job
Public sector:	Dummy; 1 if the person works in public sector
Self-employed:	Dummy; 1 if the person is self-employed

Table A2.2: Control Variables

	Natives		*Immigrants*	
	(Mean)	(Standard Dev.)	(Mean)	(Standard Dev.)
Gender	0.49	0.50	0.50	0.50
Age	42.63	11.58	41.61	10.03
Married	0.81	0.39	0.82	0.38
Have Child	0.69	0.46	0.75	0.43
Health	2.34	0.96	2.44	0.96
Part time	0.23	0.42	0.25	0.43
Public Sector	0.29	0.45	0.21	0.41
Self-employed	0.13	0.33	0.12	0.32
N	33,990	33,990	3,269	3,269

Note: Authors' calculations based on the PIAAC. A ttest applied on the mean differences between the native and immigrant samples shows no statistically significant difference in the means.

Table A2.3: Logit on Overeducation and Overskilling by Migration Status

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	0.000	-0.060***	-0.096***	-0.023***	-0.073***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.010***	0.010***	0.010	0.013***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.007)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.007	0.026***	0.047*	0.016**	0.035
	(0.007)	(0.008)	(0.027)	(0.008)	(0.027)
Have Child	-0.046***	-0.017**	-0.020	-0.026***	-0.057**
	(0.007)	(0.008)	(0.025)	(0.007)	(0.024)
Health	-0.008***	-0.009***	-0.009	-0.009***	-0.019**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.015**	0.006	0.013	0.017**	0.027
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.008*	0.012**	-0.003	0.011**	0.032*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.028***	0.006	-0.013	-0.000	-0.006
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Immigrant	0.074***	-0.085***	-0.154***	-0.119***	-0.191***
	(0.008)	(0.014)	(0.031)	(0.014)	(0.034)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country.

Table A2.4: Multinomial Logit on Skill Match Conditional on Being Overeducated

	Numeracy Skills			Literacy Skills		
	Underskilled	Matched	Overskilled	Underskilled	Matched	Overskilled
Female	0.022**	0.074***	-0.096***	-0.017	0.091***	-0.074***
	(0.011)	(0.021)	(0.019)	(0.013)	(0.021)	(0.019)
Age	0.002	-0.012	0.010	-0.003	-0.015**	0.017***
	(0.004)	(0.008)	(0.007)	(0.004)	(0.007)	(0.007)
Age Squared	-0.000	0.000**	-0.000**	0.000	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.015	-0.061**	0.046*	0.009	-0.045	0.036
	(0.013)	(0.029)	(0.027)	(0.016)	(0.029)	(0.027)
Have Child	-0.006	0.027	-0.020	0.002	0.056**	-0.058**
	(0.015)	(0.026)	(0.025)	(0.015)	(0.026)	(0.024)
Health	0.003	0.005	-0.009	-0.002	0.021**	-0.019**
	(0.006)	(0.011)	(0.010)	(0.007)	(0.011)	(0.009)
Part-time	-0.003	-0.011	0.014	0.020	-0.047	0.027
	(0.015)	(0.028)	(0.026)	(0.018)	(0.029)	(0.026)
Private Sector	0.008	-0.005	-0.003	0.006	-0.037*	0.032*
	(0.014)	(0.022)	(0.019)	(0.013)	(0.021)	(0.018)
Self-employed	-0.010	0.023	-0.013	0.005	0.002	-0.006
	(0.014)	(0.029)	(0.027)	(0.016)	(0.029)	(0.026)
Immigrant	0.085***	0.057*	-0.142***	0.121***	0.051	-0.172***
	(0.013)	(0.032)	(0.031)	(0.013)	(0.034)	(0.033)
N	5,127	5,127	5,127	5,127	5,127	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.5; * p<0.1. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country.

Table A2.5: Logit on Overeducation and Overskilling by Years Since Migration

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	-0.001	-0.060***	-0.097***	-0.023***	-0.073***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.011***	0.010***	0.011	0.012***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.007)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.006	0.026***	0.052*	0.016**	0.038
	(0.007)	(0.008)	(0.027)	(0.008)	(0.027)
Have Child	-0.045***	-0.017**	-0.021	-0.026***	-0.059**
	(0.007)	(0.008)	(0.025)	(0.007)	(0.024)
Health	-0.008***	-0.009***	-0.010	-0.009***	-0.020**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.015**	0.006	0.022	0.017**	0.033
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.008*	0.012**	-0.004	0.011**	0.030*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.028***	0.006	-0.012	-0.000	-0.005
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Years since migration:					
0-5	0.139***	-0.074***	-0.172***	-0.097***	-0.197***
	(0.026)	(0.015)	(0.034)	(0.012)	(0.031)
6-10	0.090***	-0.089***	-0.179***	-0.096***	-0.190***
	(0.021)	(0.012)	(0.034)	(0.012)	(0.034)
>10	0.052***	-0.054***	-0.064*	-0.075***	-0.075**
	(0.014)	(0.014)	(0.039)	(0.011)	(0.038)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regression weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A2.6: Logit on Overeducation and Overskilling by Immigrant Ethnic Origin

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Female	0.000	-0.060***	-0.098***	-0.023***	-0.076***
	(0.006)	(0.006)	(0.019)	(0.006)	(0.019)
Age	0.010***	0.010***	0.011	0.013***	0.018***
	(0.002)	(0.002)	(0.007)	(0.002)	(0.006)
Age Squared	-0.000***	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.007	0.025***	0.048*	0.016**	0.035
	(0.007)	(0.008)	(0.027)	(0.008)	(0.026)
Have Child	-0.048***	-0.017**	-0.019	-0.025***	-0.056**
	(0.007)	(0.008)	(0.024)	(0.007)	(0.024)
Health	-0.009***	-0.008***	-0.010	-0.009***	-0.019**
	(0.003)	(0.003)	(0.010)	(0.003)	(0.009)
Part-time	-0.014**	0.006	0.017	0.017**	0.030
	(0.007)	(0.008)	(0.026)	(0.008)	(0.026)
Private Sector	0.009*	0.012**	-0.004	0.011**	0.031*
	(0.005)	(0.006)	(0.019)	(0.005)	(0.018)
Self-employed	0.029***	0.006	-0.015	-0.001	-0.008
	(0.008)	(0.009)	(0.027)	(0.009)	(0.026)
Born in:					
Arab States	0.096***	-0.084***	-0.091*	-0.111***	-0.171***
&Sub-Saharan Africa	(0.025)	(0.014)	(0.048)	(0.011)	(0.039)
Asia	0.107***	-0.081***	-0.200***	-0.120***	-0.229***
&the Pacific	(0.031)	(0.022)	(0.041)	(0.015)	(0.044)
Latin America	0.087***	-0.063***	-0.136**	-0.049**	-0.096
&the Caribbean	(0.031)	(0.022)	(0.064)	(0.023)	(0.067)
Central	0.126***	-0.061***	-0.141***	-0.097***	-0.181***
&Eastern Europe	(0.022)	(0.018)	(0.038)	(0.013)	(0.034)
North America	-0.001	-0.060***	-0.073	-0.045**	-0.020
&Western Europe	(0.017)	(0.018)	(0.056)	(0.019)	(0.059)
N	37,259	37,259	5,127	37,259	5,127

Note: Average marginal effects are reported. Standard errors in parentheses. *** $p<0.01$; ** $p<0.05$; * $p<0.1$. Each column presents results from separate logit regressions weighted by sampling weights. Regressions are estimated in pooled sample and include country dummies. Same weight is given to each country. Reference category is natives.

Table A2.7: Logit on Overeducation and Overskilling by Age Groups

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Age 16-25:					
Immigrant	-0.019	-0.120*	-0.283	-0.219***	-0.719***
	(0.041)	(0.066)	(0.256)	(0.079)	(0.184)
N	4,222	4,222	410	4,222	410
Age 26-40:					
Immigrant	0.065***	-0.131***	-0.195***	-0.189***	-0.274***
	(0.015)	(0.023)	(0.047)	(0.024)	(0.056)
N	12,797	12,797	2,270	12,797	2,270
Age 41-55:					
Immigrant	0.082***	-0.053***	-0.126***	-0.058***	-0.129***
	(0.011)	(0.020)	(0.044)	(0.018)	(0.044)
N	14,505	14,505	1,850	14,505	1,850
Age >55:					
Immigrant	0.056***	-0.013	-0.007	-0.032	0.016
	(0.021)	(0.027)	(0.076)	(0.026)	(0.064)
N	5,735	5,735	597	5,735	597

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each panel presents separate logit regressions for different age groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A2.8: Logit on Overeducation and Overskilling by Educational Level

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Low- & Middle-Educated:					
Immigrant	0.017***	-0.067***	-0.155**	-0.106***	-0.228***
	(0.005)	(0.017)	(0.078)	(0.017)	(0.088)
N	22,236	22,236	765	22,236	765
High-Educated:					
Immigrant	0.207***	-0.111***	-0.163***	-0.139***	-0.191***
	(0.020)	(0.023)	(0.035)	(0.025)	(0.037)
N	15,023	15,023	4,357	15,023	4,357

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each panel presents separate logit regressions for different education groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A2.9: Mapping of Occupations to Skill Groups

Skill Level	*Occupation*
Skilled Occupations	Legislators, senior officials and managers
	Professionals
	Technicians and associate professionals
Semi-skilled white-collar occupations	Clerks
	Service workers and shop and market sales workers
Semi-skilled blue-collar occupations	Skilled agricultural and fishery workers
	Craft and related trades workers
	Plant and machine operators and assemblers
Elementary occupations	Elementary occupations

Table A2.10: Logit on Overeducation and Overskilling by Skill Groups

		Numeracy Skills		Literacy Skills	
	Overeducated	Overskilled	Overqualified	Overskilled	Overqualified
Skilled occ.:					
Immigrant	0.032**	-0.092***	-0.114*	-0.110***	-0.118*
	(0.013)	(0.024)	(0.064)	(0.025)	(0.067)
N	17,066	17,066	1,799	17,066	1,799
Semi-skilled white-collar occ.:					
Immigrant	0.106***	-0.047*	-0.185***	-0.103***	-0.228***
	(0.015)	(0.025)	(0.052)	(0.025)	(0.058)
N	10,758	10,758	1,929	10,758	1,929
Semi-skilled blue-collar occ.:					
Immigrant	0.049***	-0.143***	-0.164**	-0.174***	-0.235***
	(0.019)	(0.032)	(0.069)	(0.033)	(0.075)
N	6,536	6,536	1,000	6,536	1,000
Elementary occ.:					
Immigrant	0.092***	-0.109***	-0.213***	-0.125***	-0.173**
	(0.021)	(0.029)	(0.071)	(0.030)	(0.076)
N	2,899	2,899	399	2,899	399

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each panel presents separate logit regressions for different skill groups and each column presents results from separate regressions weighted by sampling weights. Regressions are estimated in pooled sample and include individual controls as well as country dummies. Same weight is given to each country.

Table A2.11: Shares of Overeducated and Overskilled Individuals in Each Country

	Belgium		Denmark		France		Germany		Ireland		Italy	
	N	I	N	I	N	I	N	I	N	I	N	I
Overeducated	11	17	14	30	11	18	11	21	16	25	20	42
Numeracy Overskilled	16	7	15	7	16	6	17	7	16	18	16	16
Literacy Overskilled	16	6	14	7	16	7	16	6	15	13	17	8
N	2,994		4,711		3,640		2,941		3,105		2,593	

	Netherlands		Norway		Spain		Sweden		UK	
	N	I	N	I	N	I	N	I	N	I
Overeducated	9	18	11	29	13	16	14	26	12	23
Numeracy Overskilled	15	3	15	7	15	10	17	5	14	9
Literacy Overskilled	15	3	15	8	16	10	16	3	14	9
N	3,475		3,077		3,114		2,699		4,910	

Note: Percentage shares of the overeducated and overskilled people among natives (N) and immigrants (I).

Table A2.12: Logit on Overeducation and Overskilling in Each Country

	Belgium	Denmark	France	Germany	Ireland	Italy	Netherlands	Norway	Spain	Sweden	UK
Overeducated	0.055**	0.113***	0.081***	0.068***	0.073***	0.170***	0.072***	0.126***	0.023	0.092***	0.082***
	(0.022)	(0.013)	(0.017)	(0.018)	(0.018)	(0.025)	(0.018)	(0.016)	(0.019)	(0.018)	(0.015)
Num. Overskilled	-0.123***	-0.108***	-0.121***	-0.129***	0.009	-0.001	-0.177***	-0.124***	-0.058**	-0.159***	-0.062***
	(0.042)	(0.019)	(0.033)	(0.037)	(0.019)	(0.028)	(0.054)	(0.030)	(0.024)	(0.033)	(0.021)
Num. Overqualified	-0.365***	-0.194***	-0.158*	-0.238***	-0.061	-0.043	-0.291**	-0.212***	-0.068	-0.262***	-0.104*
	(0.127)	(0.041)	(0.084)	(0.087)	(0.056)	(0.059)	(0.128)	(0.069)	(0.069)	(0.069)	(0.056)
Lit Overskilled	-0.131***	-0.110***	-0.100***	-0.123***	-0.027	-0.117***	-0.173***	-0.100***	-0.072***	-0.243***	-0.068***
	(0.044)	(0.018)	(0.032)	(0.037)	(0.020)	(0.037)	(0.054)	(0.027)	(0.025)	(0.044)	(0.022)
Lit. Overqualified	-0.198*	-0.214***	-0.080	-0.158*	-0.082	-0.164**	-0.340**	-0.201***	-0.103	-0.405***	-0.222***
	(0.110)	(0.041)	(0.081)	(0.081)	(0.054)	(0.068)	(0.146)	(0.066)	(0.075)	(0.083)	(0.065)
N	2,994	4,711	3,640	2,941	3,105	2,593	3,475	3,077	3,114	2,699	4,910

Note: Average marginal effects are reported. Standard errors in parentheses. *** p<0.01; ** p<0.05; * p<0.1. Each line presents results from separate logit regressions weighted by sampling weights in each country. Regressions include individual controls.

3 Long-run Patterns of Labor Market Polarization: Evidence from German Micro Data*

Abstract. The past four decades have witnessed dramatic changes in the structure of employment. In particular, the rapid increase in computational power has led to large-scale reductions in employment in jobs that can be described as intensive in routine tasks. These jobs have been shown to be concentrated in middle-skilled occupations. A large literature on labor market polarization characterizes and measures these processes at an aggregate level. However to date there is little information regarding the individual worker adjustment processes related to routine-biased technological change. Using an administrative panel data set for Germany, we follow workers over an extended period of time and provide evidence of both the short-term adjustment process and medium-run effects of routine task intensive job loss at an individual level. We initially demonstrate a marked, and steady, shift in employment away from routine, middle-skilled, occupations. In subsequent analysis, we show how exposure to jobs with higher routine task content is associated with a reduced likelihood of being in employment in both the short term (after 1 year) and medium term (5 years). This employment penalty to routineness of work has increased over the past four decades. More generally, we demonstrate that routine task work is associated with reduced job stability and more likelihood of experiencing periods of unemployment. However, these negative effects of routine work appear to be concentrated in increased employment to employment, and employment to unemployment transitions rather than longer periods of unemployment.

*This paper is co-authored by Ronald Bachmann and Colin Green.

3.1 Introduction

The past four decades have seen dramatic changes in the structure of employment. As documented by Autor, Katz, and Krueger (1998), the US witnessed a large reduction in the employment of middle-skiled workers. At the same time, there have been increases in the employment of high-skilled, and to some extent, low-skilled workers. This pattern of employment polarization has also been demonstrated for the UK by Goos and Manning (2007) and across Europe by Goos et al. (2009), and is likely to continue in the future (Autor, 2015).

These changes have been ascribed to the fact that these middle-skilled jobs involved tasks that were intensively routine in nature. As a result, they were most readily substituted with capital as computer technology became cheaper (Autor et al., 2003). This same technology is factor augmenting to high-skilled workers which in turn leads to a growth of complementary, high-skilled, non-routine intensive jobs. Along these lines, Autor et al. (1998) demonstrate that increased employment of high-skilled labor largely occurred within computer intensive industries. The growth in low-skilled employment that has occurred has also been concentrated in jobs that are not routine intensive (e.g., personal services). One argument is that this reflects a compositional change in consumption due to the increase in high-skilled workers (Mazzolari & Ragusa, 2013).

This literature provides a compelling view of the impact of structural change on the labor market over the past four decades. This said, the existing empirical evidence largely takes the form of comparisons of decade upon decade employment numbers and shares at aggregated levels of occupational detail. Until recently, the dynamics of employment transitions implicit in the process of polarization have been inferred from comparisons of these cross-sectional changes. A large US literature has developed that uses micro data to examine the contribution of different flows to the evolution of employment polarization. For instance, both Jaimovich and Siu (2012) and Smith (2013) highlight the decline in inflows to routine work particularly from unemployment. The latter paper further provides some evidence of increases in inflows into high-skilled and low-skilled employment, and more generally that overall job finding rates into non-routine jobs have been rising. Along similar lines, Cortes, Jaimovich, Nekarda, and Siu (2014) examine which specific labor market flows can account for rising job market polarization. They find that the disappearance of routine jobs is mainly due to falling worker flows from both unemployment and non-participation to routine employment, and to rising worker flows from routine employment to non-participation. For Germany, Bechara (2017) finds that the employment contraction in routine occupations is largely attributable to young workers and women who increasingly leave routine-intensive jobs and subsequently enter other occupations or into non-participation.[1]

In practice, little is known regarding the actual process of job-loss and reemployment at the individual worker level, particularly the nature of individual worker transitions that result from the reduction in demand for routine intensive work. This seems an important gap in our knowledge as any potential losses due to this pattern of structural change is likely to be most concentrated among routine workers. An exception is the recent paper by Cortes (2016) who uses the Panel Studies of Income Dynamics (PSID) to look at long-run effects of labor market polarization in the US. He finds evidence of selection on ability for workers switching out of routine jobs. In particular, while low-ability routine workers are more likely to switch to non-routine manual jobs, high-ability routine workers are more likely to switch to non-routine cognitive jobs. With respect to wages, his results suggest that workers staying in routine jobs experience less wage growth than workers staying in any other type of occupation. This is characterized by a reduction in the wage premium for routine occupations of 17% between 1972 and the mid-2000s. Furthermore, Cortes et al. (2014) use CPS data to analyze what role labor market flows play for the disappearance of routine jobs in the US since the 1980s.

This paper uses administrative data for Germany to characterize the individual level patterns underlying the process of labor market polarization. Our data is particularly well suited to addressing these issues as it allows us to follow individuals across a long span of time. Specifically we can examine individual level transitions but also how these have changed over the past 4 decades. In doing so we provide evidence on the secular pattern of polarization over a long time period at a high frequency of observation. As a result, we can characterize the evolution of polarization over time. In addition, we provide evidence on a

[1] In contrast to our paper, Bechara (2017) focuses on occupational inflow and outflow rates at the 2-digit level as well as differences between men and women in this context.

range of individual level job transitions. Initially, we provide descriptive evidence on the relative job stability, unemployment experiences and job-to-job transitions for routine task intensive workers. We then move to multivariate analysis in an attempt to assess the role of compositional effects. Finally, we provide suggestive evidence on welfare losses, in terms of unemployment duration and job instability related to employment polarization.

The contribution of our paper to the existing literature on routinization is therefore twofold. First, we are, to the best of our knowledge, the first to provide encompassing micro evidence on the long-run effects of labor-market polarization for a European country, thus complementing the evidence provided by Cortes (2016) and Cortes et al. (2014) for the US. Second, our analysis goes beyond the existing literature by providing detailed evidence on the nature of the labor market experiences of routine workers, also taking into account occupation-specific measures of task intensity that vary over time. This type of analysis is only possible with the type of panel data at our disposal, which we complement with survey information on occupational task content, i.e. routine intensity.

The paper is structured as follows. In the next section, we provide information on the data used including the administrative data set as well as the data on the task intensity of different occupations. The third section presents the empirical methodology, while the fourth section reports and discusses the results, and the final section summarizes and concludes the discussion.

3.2 Data

3.2.1 Worker-level Data

Our main data source is the Sample of Integrated Labor Market Biographies (SIAB) for 1975-2014, which is provided by the Institute for Employment Research (IAB). The SIAB is a representative 2% random sample of the Integrated Employment Biographies (IEB) which contains the labor market history of all individuals in Germany that are employed subject to social security contributions, those in part-time employment not earning enough to make social security contributions, those receiving unemployment or social benefits, and those officially registered as job-seeking at the German Federal Employment Agency or participating in programs of active labor market policies. Civil servants and self-employed workers are not included in the data.[2] The information on labor market states is exact to the day. A detailed description of the Sample of Integrated Labor Market Biographies is provided in vom Berge, König, and Seth (2013).

The SIAB provides information on workers' employment status, age, gender, occupation and education as well as limited information on establishment characteristics (economic sector, establishment size). This data set is representative for all dependent-status workers, and contains information on all employment and unemployment spells of the workers covered. From this sample, we further exclude, apprentices, trainees, homeworkers, and individuals older than 65.[3] In line with previous research, we focus on male full-time workers aged 18-65. As our period (1975-2014) covers the pre-unification period, we focus on West Germany only.

The data allows us to characterize individuals as being in one of three labor market states at any point in time: employment covered by social security (E), unemployment with benefit receipt (U), and non-participation (N). Non-participants are those individuals not recorded in the data sets. Therefore, this state includes those workers out of the labor market, as well as workers not covered by social security legislation, e.g., civil servants and self-employed workers.

Because of the way the data are collected, both establishments' reports of a new employee and individuals' notifications of moving into or out of unemployment may not be exactly consistent with the actual change of labor market state. For example, workers might report to the unemployment office only a few days after they are laid off. We take this potential measurement error into account in the following way: If the time lag between two employment spells at different establishments does not exceed 30 days, this is defined as a

[2] Caliendo and Uhlendorff (2008) find that only 3% of all non-employed workers and only 1% of all wage-employed workers in Germany enter the state of self-employment annually, implying that transitions into and out of this state only play a minor role for our analyses.

[3] Excluding part-time workers from our sample and treating them as non-participants artificially increases our transitions into and out of non-participation. However, as the SIAB data only distinguish between two categories of part-time employment and the number of working hours can be relatively low, we decided to focus on core full-time workers.

direct transition between the two states recorded. We count it as an intervening spell of non-employment if the time interval between the two records is larger than 30 days.

Since the data set used contains daily information on the employment and unemployment history of every individual in the sample, it is possible to calculate worker flows taking into account every change of labor market state that occurs to an individual within a given time period. We are thus able to compute the flows between employment and non-employment, as well as direct job-to-job transitions (EE flows) using the establishment identification number.

3.2.2 Measuring Routine Intensity and Related Worker Flows

The analysis of the employment consequences of routinization requires the classification of employment into occupations according to task types. In the literature there exist two broad approaches to this. The first is a parsimonious approach as per Goos and Manning (2007), Goos et al. (2009) and Cortes (2016) whereby workers are assigned to routine, non-routine manual and non-routine cognitive categories based on groups of standardized occupational codes. A chief virtue of this approach is that it does not require the measurement of task content at an occupational level, while using relatively aggregated occupational information makes this approach more robust to periodic reclassifications of disaggregated occupational classifications. This comes at the potential cost of the introduction of measurement error due both to within-occupational variation in task intensity, and changes in occupational task intensity over time.

The second approach, as in Autor et al. (2003), relies on occupational task analysis from additional sources to classify jobs in terms of task intensity. In the US context, this comes from the Dictionary of Occupation Titles (DOT) (and later O*NET) information on the task composition of occupations. This information is generated from periodic expert evaluations of job task content. This approach more clearly mitigates some of the issues of measurement error inherent in the first approach. However, the relative infrequency of DOT still leads to likely variation between the defined task content of an occupation and what tasks any given worker's job is likely to actually consist of as one moves further away from the DOT date.

One of the aims of the O*NET replacement was to limit this information lag by providing more frequent job task information.

In the German context, the main approaches used in the literature to date can be viewed as alternatives of this DOT approach where, instead of expert evaluations, survey-based information on task content is used. This reflects the availability of data from BIBB/IAB and BIBB/BAuA Employment Surveys (herein BIBB data) that provide a representative sample of workers and include questions regarding the task content of jobs.[4] In previous work, three different task intensity measures have been generated using this data. Spitz-Oener (2006) and Antonczyk et al. (2009) generate different measures of relative task intensity at occupation levels using worker self-reports on the task content of their work. While Baumgarten (2015) computes an alternative measure of routinization focusing on the use of tools on the job.

We follow the approach of Antonczyk et al. (2009) and categorize the activities employees perform at the workplace into routine (R), non-routine cognitive (NRC) and non-routine manual tasks (NRM). This is computed for 54 occupational categories following Tiemann et al. (2008), and for each occupation-time period combination provides a R, NRC and NRM share that sums to 100%. This measure can be expressed as:

$$TI_{ijt} = \frac{\text{number of activities in category } j \text{ performed by } i \text{ in cross section } t}{\text{total number of activities performed by } i \text{ over all categories at time } t} \tag{3.1}$$

As an example, for routine tasks, this implies taking the number of routine tasks performed by a person at a specific point in time, and relating this to the total number of activities performed in all task categories (routine, non-routine manual and non-routine cognitive). Taking the averages of individual task intensities provides a continuous measure of Routine Task Intensity (RTI) over time for a given occupational group.[5]

A key advantage of this data is that the survey is conducted at regular six to seven year intervals throughout our period of analysis (1979, 1985/86, 1991/92, 1998/99, 2006 and

[4]Details about how we deal with the different waves of the task data set are spelt out in the appendix.

[5]In unreported estimates we use the alternative approach set out by Spitz-Oener (2006). The nature of our results are largely unaffected by this.

2012). This allows us to have time-varying task intensity by occupational groups. As mentioned above, earlier literature has tried to explain the long-term relative decline of different task intensities, while other research has focused on quite short periods. In both cases this leads naturally to an approach where occupation task intensity is fixed at an initial or pre-sample period. A focus of our paper is how worker outcomes at a particular time period are influenced by exposure to different task mixes. Hence, it seems inappropriate to, for instance, examine outcomes of workers in the 1990s based on the task intensity of their occupation fixed at 1979 values. Our main approach is to use the BIBB data to update occupation task intensities over time. This has the advantage that worker outcomes are evaluated more closely to their actual task composition at the time of observation.

A cost of this approach is that, when compared to using initial task values only, there is the potential of marked discontinuities in the task intensity shares at BIBB survey dates. These are not large in practice in terms of continuous measures of task intensity. However, any analysis that, like previous work, is based on categorising workers into different, discrete task intensity groups (e.g., R, NRM and NRC) faces a naturally greater probability of discontinuities at BIBB survey dates in the proportion of occupations (and hence workers) belonging to any given task group. We use a number of approaches to dealing with this issue, but stress that none of these choices 'drive' our results. Initially we provide descriptive evidence that aims at being comparable with longer, but 'snapshot' based, evidence for the US, UK and elsewhere. In doing so, we adopt a similar approach to this particular strand of the literature and fix occupations into three categories at the start of the data. These categories are:

1. Routine (R): Administrative support, operatives, maintenance and repair occupations, production and transportation occupations (among others).
2. Non-Routine Cognitive (NRC): Professional, technical, management, business and financial occupations.
3. Non-Routine Manual (NRM): Service workers.

Our next step is to try to examine the evolution of worker outcomes over the periods, focusing on two sets of complementary outcomes. First, we seek to provide results on the effect of RTI on the employment probabilities of workers over the short run (1 year) and long run (5 years). Note that this means that our analyses using the RTI measure start in 1979, whereas the analyses using the three task groups start in 1975; furthermore, the analyses following individual workers for 5 years stop in 2008 in order to avoid the problem of right-censoring. We then subsequently extend this to duration modelling of the effect of RTI on labor market transitions more broadly. In both of these cases, we use RTI as a continuous measure. We deal with the issue of revisions of occupational task shares across BIBB waves by splitting our data into a number of BIBB-Survey data specific periods (e.g. 1979-1984; 1985-1991; 1992-1998; 1999-2005; 2006-2011 and 2012 to present). This allows us to provide evidence on how the effect of task intensity on worker outcomes has changed over the past 3 decades. We again stress, however, that the main thrust of our findings are not materially affected by alternative approaches such as pooling our data across the whole survey period.

3.3 Methodology

3.3.1 Descriptive Evidence

We first provide descriptive evidence that aims to paint a picture of the labor market situation of workers according to the task content of their work. Specifically, we provide univariate descriptive statistics on the evolution of task-specific employment shares and unemployment rates, and transition rates between different labor market states and task categories. We exploit a particular strength of our data and examine how these patterns have changed over a long period.

In the first step of our descriptive analysis, we provide evidence on employment stocks for the three task categories. To aid comparability over time we adopt a variant of the classification approach used by Cortes (2016) and group occupations into task categories that are fixed across time. This has the additional benefit of allowing us to more readily compare changes in occupational/task structure in Germany to existing evidence for the US and elsewhere. We then turn to the BIBB data to provide evidence where, as described above, we allow the task shares of given occupations to vary reflecting underlying changes in job content over time. The distribution of each task type for each wave is provided using the occupation-level employment shares from the BIBB survey data. Finally, we take the occupational level task measures generated from the BIBB data to the SIAB data. This allows the task shares of employment to vary in between BIBB waves according to annual changes in occupational employment. This, in theory, allows for any cyclical variations in task shares to be apparent. In practice, all three approaches provide an estimate of the share of tasks in the labor market at a point in time. As we discuss in the results, these are not always entirely congruent, but provide similar views on the change in task shares over the entire period.

We then proceed from this to examine worker transitions between labor market states, again paying particular attention to the three task groups. In order to do so, we first display a transition matrix between workers employed in the different task groups and unemployed workers who were previously employed in these three task groups. This provides evidence on the probability of a switch between task groups, both directly (job-to-job) and indirectly (through unemployment). Next, we compute the probability of job exit by task group over time. This yields a measure of job stability for routine, non-routine manual and non-routine cognitive workers. We then examine where workers who have separated from their previous job, and who make a direct job-to-job transition, end up in terms of task category. In a similar vein, we provide evidence on unemployed workers according to the task affiliation in their previous job. We thus show the evolution of the unemployment exit rates by task type over time, as well as the destination task groups where workers end up.

3.3.2 Econometric Analysis

With this as initial information, we then examine how the employment probabilities of workers with a given RTI evolve over the short (1 year) and medium (5 years) term. In order to investigate the determinants of these employment probabilities, we estimate logit models of the form:

$$Pr[y_{it} = 1 \mid x_{it}, \beta, \alpha, \gamma] = \Lambda(\alpha_i + RTI_{it}\beta + x_{it}\gamma) \tag{3.2}$$

where $\Lambda(.)$ is the logistic cdf with $\lambda(z) = ez/(1 + ez)$. x_{it} is a vector of individual- and job-specific variables including age, skill level, economic sector, firm size, region (Bundesland) fixed effects, month dummies, as well as the regional unemployment rate. To avoid issues regarding discontinuous changes in RTI due to changes in BIBB based classifications we stack observations from each BIBB year (1979, 1985, 1992, 1999, 2006, 2012). As a result, RTI is the routine task intensity of ith individuals job at time t described in Equation (3.1) above. β is the coefficient of interest and provides the conditional (average) effect of RTI on an individual's future employment probability. We include BIBB wave dummies in all models.

In the empirical results, we extend Equation (3.2) in a number of ways. One main extension relates to time variation and non-linearities in task effects. Estimates of β provide the average effect of RTI on employment outcomes of workers across our period of observation. A main interest is in how this has changed over time. To examine this, we first interact RTI with a time trend. This provides an estimate of changes in the employment effect of RTI over time. We subsequently include industrial sector – time interactions to isolate this RTI-time effect separately from sector – year specific shocks to employment.

Any differential patterns in employment by task group that are revealed reflect a range of underlying types of labor market transitions, including those related to job loss and re-employment patterns. To examine this we again provide descriptive evidence related to job loss rates and re-employment rates by task group. This is provided overall and by decade, and with a focus on the extent to which re-employment occurs within the same task type or via transitions to alternative types. This is important as it provides evidence of where routine job workers go after job loss. Do they experience lower re-employment probabilities (and hence are more likely to experience longer unemployment durations)?

Examining this again leads directly into multivariate analysis. The most appropriate approach is to estimate models that recognize the underlying duration nature of the data. This leads to the estimation of hazard rate models. As our dataset contains daily information on individual workers' employment histories, we use a semi-parametric specification in continuous time, i.e., a piecewise-constant exponential (PCE) model. As the PCE model is a proportional hazard model, the conditional hazard rate of leaving employment $\lambda(t|X, RTI)$ satisfies the separability condition:

$$\lambda(t \mid x_{it}, RTI_{it}) = \lambda_0(t) exp(\gamma x_{it} + \beta RTI_{it}) \tag{3.3}$$

where x is a vector of individual, potentially time-varying, characteristics, and λ_0 denotes the baseline hazard. Again, RTI measures the task intensity of the ith worker's job and β is the parameter of interest. The PCE model assumes that the baseline hazard is constant within a specified time interval, and thus follows a step function with k segments.

$$\lambda_0(t) = \lambda_j, \qquad a_{j-1} \leq t < a_j, \qquad j = 1, \ldots, k. \tag{3.4}$$

We specify six such segments: 0 to 30 days of employment duration, 31 to 182 days, 183 to 365 days, 366 to 1095 days, 1096 to 2920 days, and more than 2920 days. We estimate Equation (3.3) separately for job-to-job, job-to-unemployment transitions, and unemployment-to-job transitions. The first set of estimates provides an estimate of the impact of RTI on overall job stability. The second relates to the potentially most negative outcome, job loss coincident with unemployment. While the last provides estimates of the effect of RTI on ongoing difficulties in re-entering employment. An issue with this last set of estimates is how to define an unemployed individual's RTI. Our approach is to use the RTI of their last employment spell. This has the added effect that we can only estimate these models for unemployed individuals who we observe in our data in a job prior to this.

Even though we control for a wide array of observable characteristics, the hazard rates of observationally equivalent individuals may still differ from each other. Ignoring such unobserved heterogeneity in duration models produces incorrect results (cf. Lancaster (1992)). To account for unobserved heterogeneity, the proportional hazard model is extended to allow for a multiplicative unobserved heterogeneity term u, which yields a mixed proportional hazard model.[6] The hazard function then becomes:

$$\lambda(t \mid x_{it}, RTI_{it}, u) = \lambda_0(t) exp(\gamma x_{it} + \beta RTI_{it}) \tag{3.5}$$

[6] See van den Berg (2001) for a survey of this model class.

where u follows a Gamma distribution (Abbring & van Den Berg, 2007) and is assumed to be independent of regressors and censoring time. The heterogeneity term is shared across different spells of a given individual, causing observations within groups to be correlated.

In all duration models our control vector, x, largely follows that for Equation (3.2). We include industry, region, year fixed effects and regional unemployment rates to capture differences in economic conditions over time and across regions. Again, we explore time variation and non-linearities in the effect of exposure to different levels of RTI on labor market outcomes.

3.4 Results

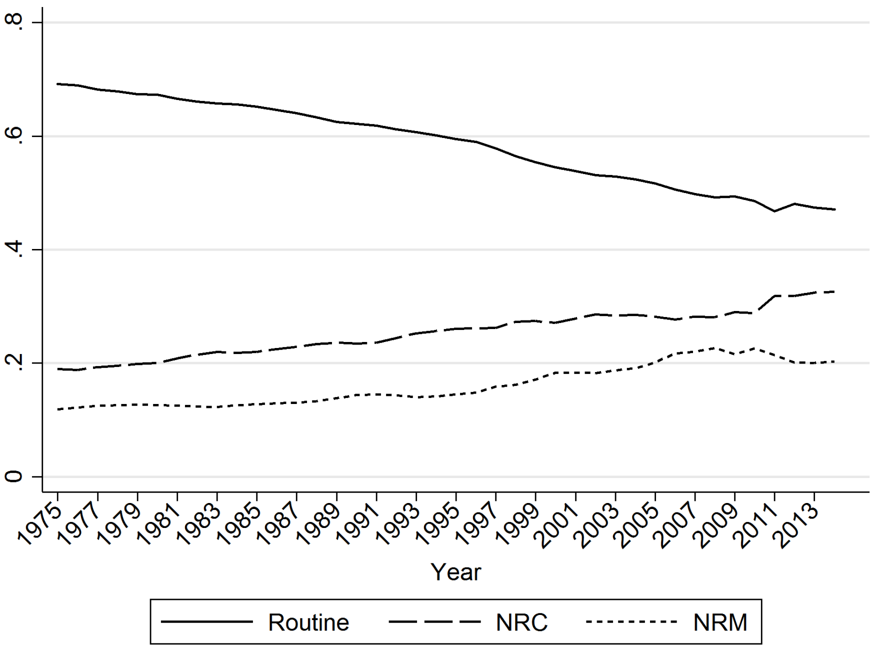
3.4.1 The Evolution of Task Shares and Intensities 1979 to 2013

Figure 3.1 displays the annual employment shares by task type for the period 1975 to 2014 based on the initial, Cortes style, classification approach. The employment share of routine jobs has strongly declined over the time period under observation, from 69% in 1975 to 48% in 2014. This represents a dramatic reduction in the employment share for these types of jobs. By contrast, the employment shares of non-routine manual tasks have increased from 12% to 20% and non-routine cognitive tasks increased from 19% to 32% during the same time period. Again, this fits broadly with the existing evidence for other countries.[7]

The relatively smooth nature of this process over the period is also noticeable. Our data suggest that polarization has been an on-going gradual process in Germany. Moreover, there is little evidence of substantive cyclical variations, or at the least these variations are dominated by the secular patterns. This is important as, based on decennial comparisons, the existing literature has sometimes suggested that polarization has been concentrated in specific decades or episodes. At the same time previous research that focuses on relatively

[7] For instance, Goos, Manning, and Salomons (2014) find for 16 European countries that while the employment shares of the highest-paying occupations (mainly characterized by non-routine cognitive tasks) have increased over the time period 1993-2010, the employment shares of the middle-paying occupations (mainly routine jobs) have declined.

Figure 3.1: Employment Shares of Task Categories, 1975-2014, Men



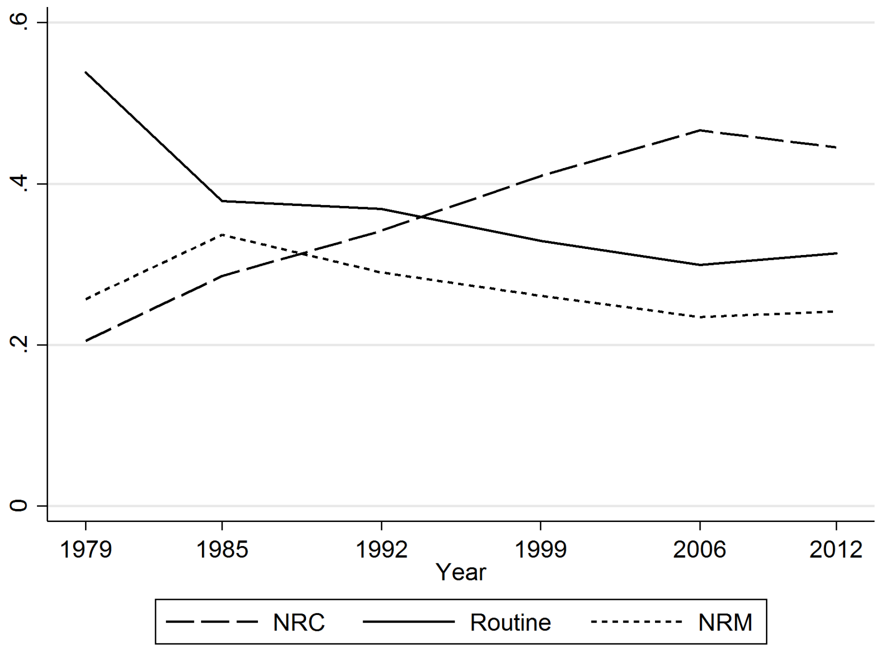
Source: SIAB 1975-2014, own calculation.

short periods has suggested that business cycle dynamics may speed up the polarization process.

As an alternative view of the same process, Figure 3.2 provides the average share of workers' job task intensities across the 6 BIBB waves. These numbers result, in effect, from computing the intensities of R, NRC and NRM tasks from the BIBB survey data. This differs from Figure 3.1 insofar as (a) it provides a measure of overall "routineness" of work across time (and of the overall intensity in NRC and NRM) and (b) by using the BIBB information we allow the task intensities of any given occupation to change over time. Nonetheless, the general view is the same. There has been a marked reduction in routine task intensity over the past 35 years. The drop is steady from 54% of all tasks in 1979 to about 30% in 2006. After this point there is essentially no change in the routine task share.[8] Despite the high frequency of the BIBB surveys, the task intensities sometimes change markedly at the beginning of each BIBB period. The reason behind is twofold. First, holding the task

[8]In addition to our baseline approach, we applied further specifications to estimate the task intensities. The decreasing pattern of routine task intensity is visible in all approaches. See Figure A3.1 for more detail on the different approaches applied.

Figure 3.2: Average Task Intensities of Employment from BIBB Data



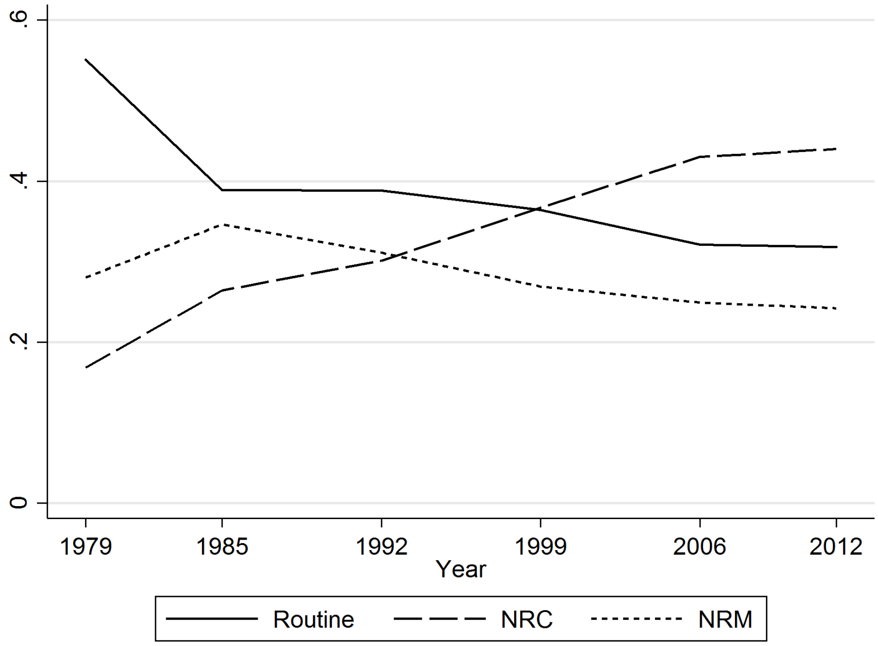
Source: BIBB/BAuA/IAB, own calculation.

intensities constant within the BIBB periods ignores within-occupation changes and causes a large change at the period beginnings. Second, the questions in the BIBB surveys vary to some extent over time. We therefore focus on the survey questions that are repeated across waves, and furthermore merge specific questions with similar content to adjust the number of questions in order to obtain a similar number of questions in each wave and task category.

Finally, Figure 3.3 reports the routine task share where we weight the BIBB occupation task share by the SIAB employment data. As both represent samples of the same underlying population, the overall patterns of the evolution of task shares are quite similar. However, this approach allows for within BIBB period variation in task shares and hence variation from more short-term employment changes. Taken together this provides a body of evidence that there has been a quite dramatic reduction in routine-intensive tasks in Germany since the 1970s.

Are these changes in task shares associated with differing worker compensation over the period? Table 3.1 presents unconditional mean differences of wages according to task group.

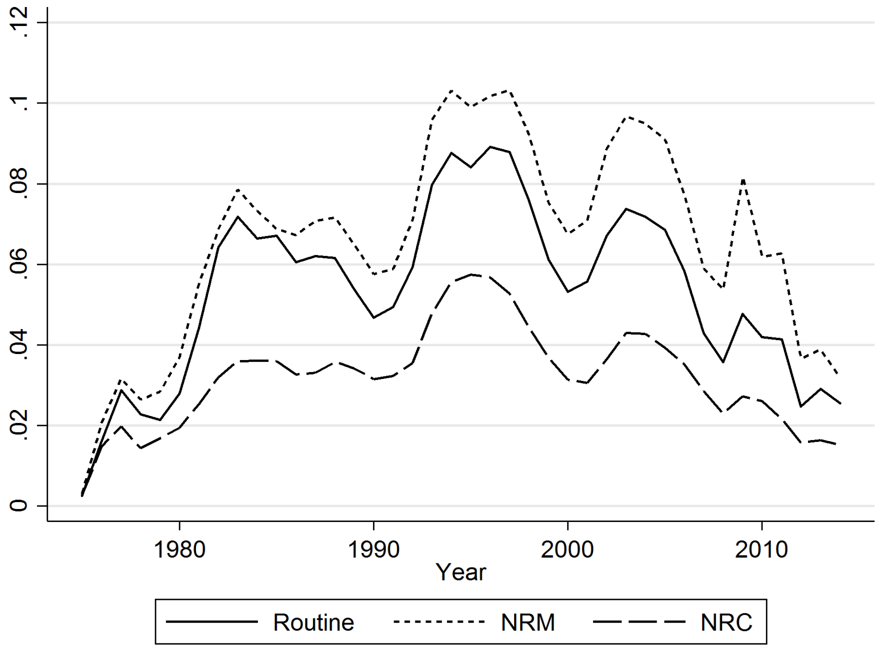
Figure 3.3: Average Task Intensities of Employment from the IAB Data, 1979 to 2012



Source: SIAB 1975-2014, own calculation.

A number of points are worth emphasizing. The pattern for wages shows a clear ordering of non-routine cognitive workers, routine workers then non-routine manual workers. This fits with the distribution of these skills predominantly over high-skilled, middle-skilled and low-skilled occupations, respectively. More importantly, these wage gaps appear to be increasing over time. This, when combined with the earlier evidence is suggestive of a process of quantity adjustments (employment) to labor demand for routine tasks workers.

Figure 3.4: Task-specific Unemployment Rates, 1979-2014



Source: SIAB 1975-2014, own calculation.

Table 3.1: Average Wages by Task Group, 1975-2014

	Routine	NRC	NRM	Overall
1970s	81.65	101.29	75.76	85.06
1980s	89.65	115.41	81.93	94.83
1990s	100.40	130.40	89.99	107.24
2000s	101.65	137.31	85.98	110.33
2010s	99.16	137.24	85.29	110.61
Total	94.87	127.30	84.90	

Source: SIAB 1975-2014, own computation.
Note: Wages refer to daily wages in Euro for the time periods 1975-79, 1980-89, 1990-99, 2000-09, 2010-14, and 1975-2014 (total).

Given these reductions in employment, an obvious question to ask is whether this has led to changes in the unemployment levels associated with previously being in a given job-task category. Figure 3.4 reports task-specific unemployment rates over time. Non-routine cognitive workers and non-routine manual workers feature the lowest and highest unemployment rates, respectively, while the unemployment rate of routine workers is between these two across the period.

3.4.2 Descriptive Evidence on the Links between Tasks and Employment Transitions

We next provide descriptive evidence on labor market transitions according to job tasks performed by workers. These are most readily reported using discrete categorization of workers into routine, non-routine manual and non-routine cognitive groups. The most straightforward means of doing this is, again, in the spirit of Cortes et al. (2014). Table 3.2 provides evidence regarding the transition probabilities from one year to the next between employment in different task types, unemployment, and non-participation. Employment probabilities are highest for non-routine cognitive workers, followed by routine workers and non-routine manual workers. The latter workers also fare worst in terms of job-finding probabilities. Somewhat surprisingly, routine workers have the highest job-finding probabilities, which seems to be an indication of a high level of churning for this type of worker.

Table 3.2: Transition Matrix Between Different Labor Market States and Task Categories

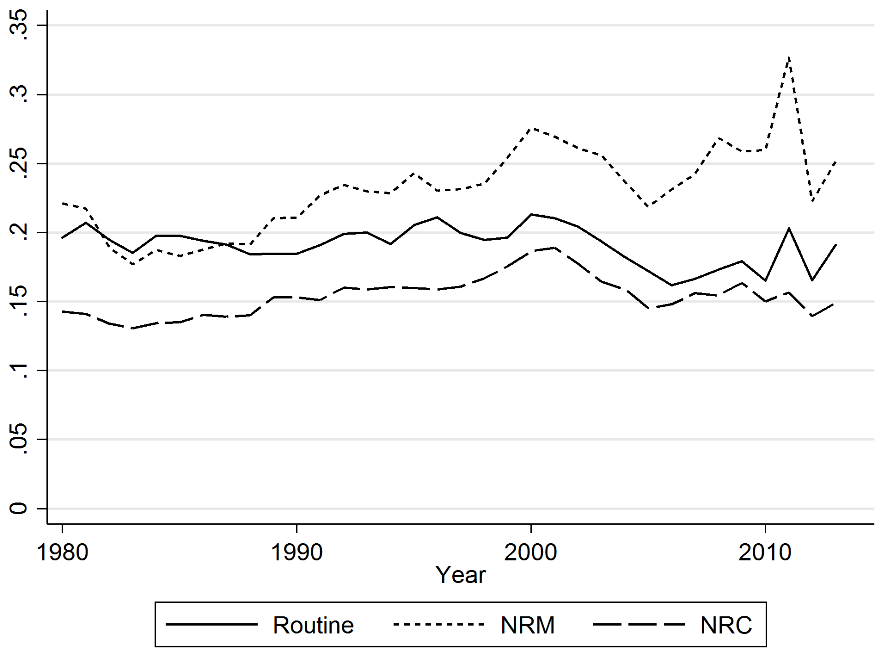
		Year t+1				
		Employment			Unemployment	Non-Participation
		Routine	NRC	NRM		
	Employment					
	Routine	90.8	1.28	1.33	2.95	4.37
	NRC	2.02	92.23	0.57	1.91	3.27
	NRM	5.69	1.39	83.04	4.06	5.82
Year t						
	Unemployment					
	Routine	21.64	3.38	5.48	56.91	12.59
	NRC	8.07	17.83	3.13	60.01	10.97
	NRM	12.53	2.9	12.56	56.53	15.48

Source: SIAB 1975-2014, own computation.

It also becomes apparent that direct changes between different task categories for employed workers are uncommon, the corresponding annual transition rates are generally below 2%.

An exception to this are transition rates from non-routine manual to routine employment, which amount to nearly 6%. Switching task categories is more common for unemployed individuals, although still relatively low. For example, the probability that a (previously) routine worker who is unemployed finds a job as a non-routine cognitive worker is 3.38%. Again, the transition rate from (previously) non-routine manual workers to a routine job is the exception. Non-routine manual workers who are unemployed display an equal probability of being in non-routine manual work and of being in routine work one year later.

Figure 3.5: Probability of Job Exit, by Task Categories, 1980-2014

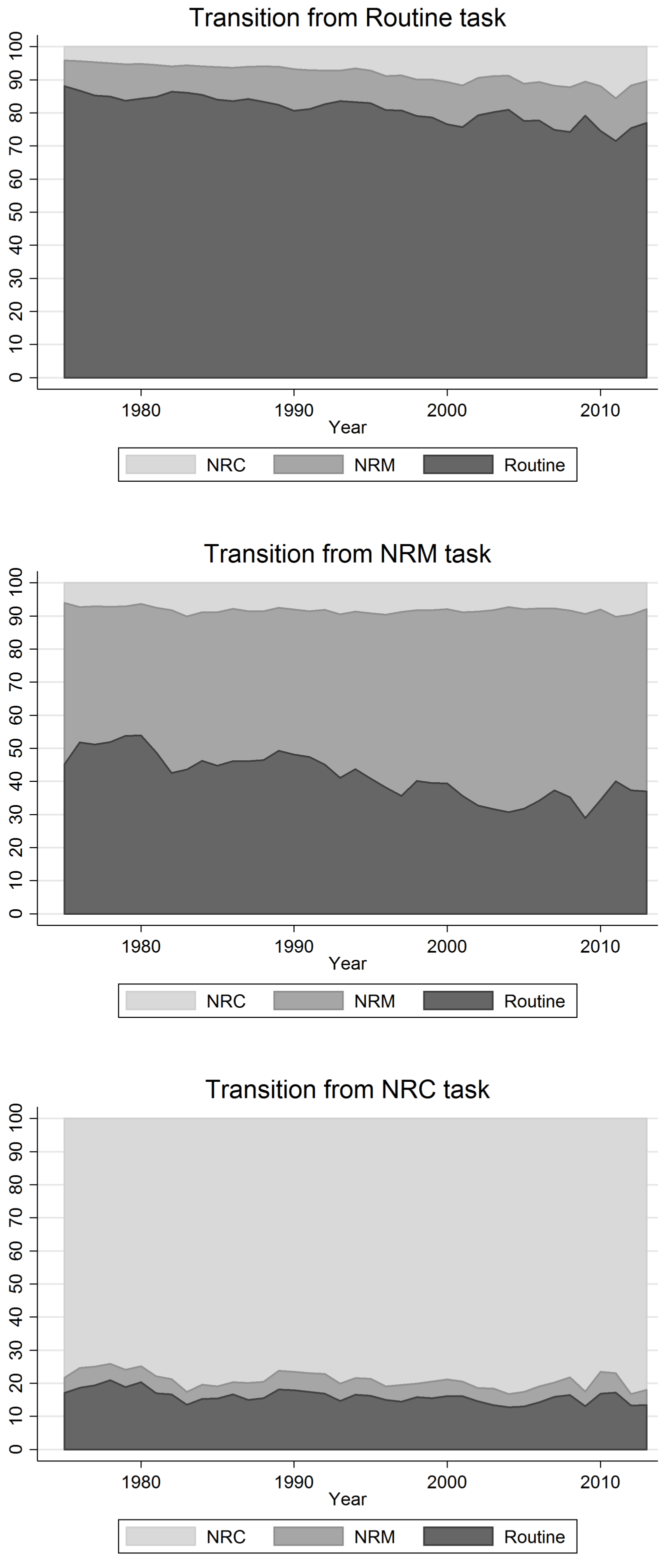


Source: SIAB 1975-2014, own calculation. Job exit defined as making a transition to a different establishment, a different task category, or to unemployment.

Figure 3.5 provides additional information regarding transitions over time by task type. Specifically, it provides the probability of a job episode ending according to a worker's task type. The main driving force behind these job exit probabilities seem to be cyclical during most of the observation period, e.g., with an increase during the bursting of the dot-com bubble of the early 2000s. In a similar vein to Figure 3.1, non-routine manual workers have the highest probability of job exit across the period of 1980-2010. Routine workers have lower job exit probabilities than non-routine manual workers, but higher exit rates than non-routine cognitive workers.

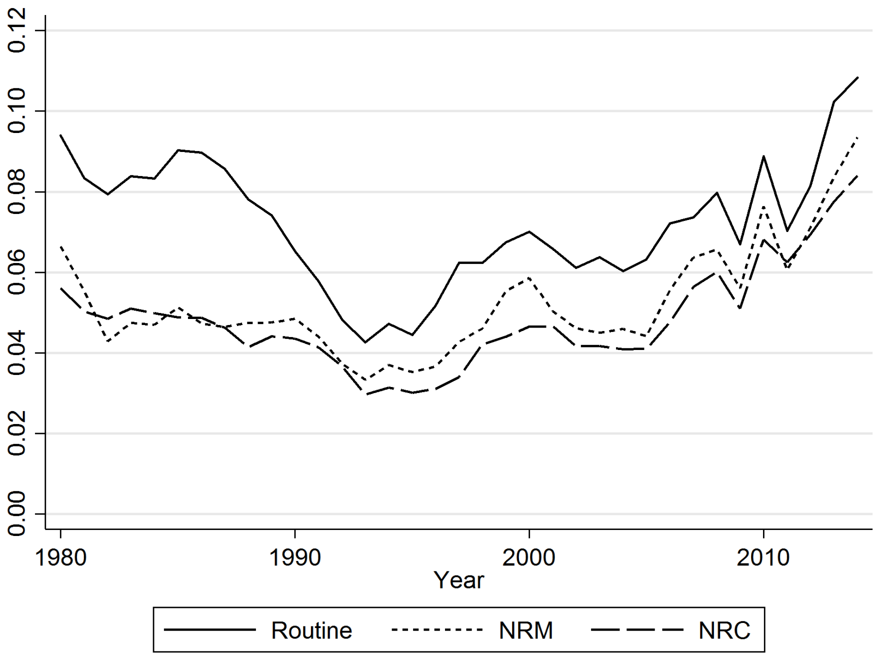
Figure 3.6 provides information on transitions conditional on a worker making a job-to-job transition and according to their initial task type. For each task type there are high levels of state dependence. A worker who makes a transition is substantially more likely to move to another job in the same task category. More importantly, there is evidence that this level of state dependence has increased over time for two task types. Both non-routine cognitive and non-routine manual workers are more likely to transit between jobs in the same task type at the end of our observation period than at the start. This appears to follow a steady path over time, and is most marked for non-routine manual workers. At the same time, routine workers witnessed a marked reduction in this state dependence. Moreover, this change appears to have been driven at least partly by transitions into non-routine cognitive work. This provides evidence that part of the patterns seen earlier in Figures 3.1, 3.2 and 3.3 reflect differences in transitions across tasks.

Figure 3.6: Transition Shares from Employment, Conditional on Making a Transition, by Task Categories, 1975-2014



Source: SIAB 1975-2014, own calculation.

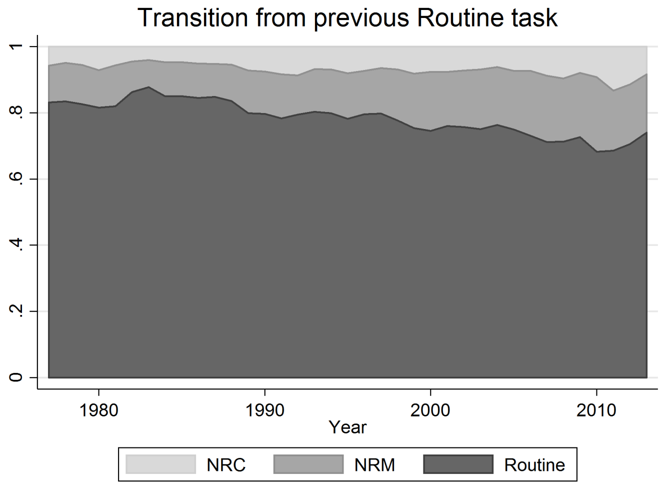
Figure 3.7: Unemployment Exit Rate, by Task Category, 1979-2014

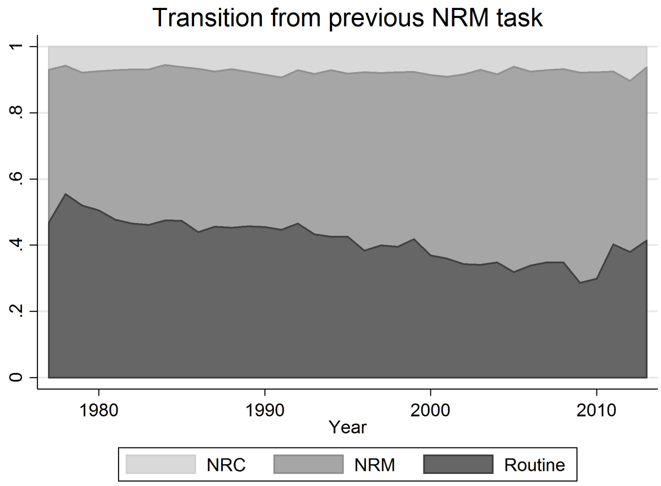


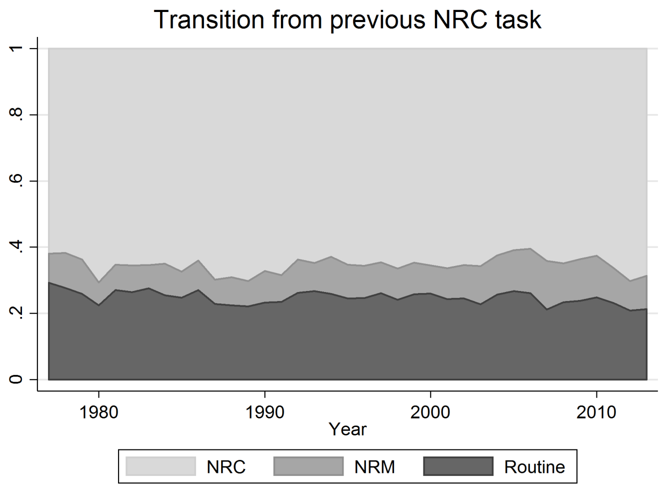
Source: SIAB 1975-2014, own calculation.

Turning to workers who have become unemployed, Figure 3.7 features the unemployment exit rate of workers in the three task categories. First, unemployment exit rates show a marked decline in the 1980s and early 1990s, reflecting the structural worsening of labor market conditions in Germany. Since the mid-1990s, and particularly since the mid-2000s, this trend has been reversed with unemployment exit rates constantly increasing, which is in line with the strengthening performance of the German labor market highlighted by Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014). Somewhat surprisingly, previously routine workers are the most likely group to exit unemployment over the entire observation period. Figure 3.8 shows that these unemployed workers mainly return to a routine job. Non-routine manual workers also largely return to the same task category after a spell of unemployment, however with a much lower probability. Many of them actually switch to routine jobs, even though the transition from non-routine manual unemployment to routine employment has become less frequent over the observation period. For non-routine cognitive workers, there is also strong state dependence, with no obvious time trends.

Figure 3.8: Transition Shares from Unemployment, Conditional on Exiting Unemployment, by Task Category, 1975-2010







Source: SIAB 1975-2014, own calculation.

3.4.3 Labor Market Histories over the Short and Medium Run

We now turn to multivariate estimation of the effect of RTI exposure on employment. Employed workers are stacked in 6-7 year intervals (i.e., according to the BIBB wave years described above: 1979, 1985, 1992 etc.) in order to estimate the probability of remaining in employment after 1 year and 5 years, respectively, using the logit model described in Equation (3.2). We include a range of controls along with our variable of interest, the RTI of the job. Estimation results are presented in Table 3.3. The first column provides the average conditional effect of RTI exposure on employment probability at t+1. This demonstrates that higher RTI is associated with a lower probability of still being in employment one year in the future. The corresponding marginal effect amounts to -0.026. Since RTI is measured on a 0-1 continuum, this marginal effect can be interpreted as a 2.6 percentage point reduction in the likelihood of being employed one year later if a worker moved from a job with zero routine task intensity to a job that is entirely routine. As such a change in RTI is unrealistic, we compute the change in employment probability if the RTI of a job increases by one standard deviation. The standard deviation of RTI across our time period is 0.202, hence a one standard deviation increase in RTI is associated with a decrease in the likelihood of being employed one year later of 0.53 percentage points (2.6 * 0.202). Given that the mean rate of employment loss over one year amounts to 13 percent, this can be viewed as a small, but substantial, reduction in employment probability due to a worker being exposed to RTI tasks.

Column (2) displays results that extend this to ask whether this RTI penalty has changed over the sample period. It reports coefficients on RTI and RTI interacted with a time trend. Whilst caution must be taken with adding interaction and main effects in a non-linear model, the signs and relative magnitude of these terms are informative. The initial RTI effect, which can be interpreted as the effect of RTI on employment stability at the start of our period, is essentially zero. RTI exposure was unrelated to employment stability in the late 1970s. The interaction term suggests that this changed over the past decades. Interpreting interaction terms in non-linear models is difficult. To provide a rough guide, we re-estimated this model using a linear probability model. The estimates suggest that a worker who was in an entirely routine job (i.e. RTI intensity = 100 per cent) would face an annual decrease in 1 year

Table 3.3: Routine Task Intensity of Current Job and Probability of Employment after 1 Year and 5 Years, 1979-2013, Logit Odds Ratios

	After 1 Year			After 5 Years		
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	0.732***	1.055	0.993	0.706***	0.800***	1.326***
Time	0.990***	1.055***	0.940***	0.384***	0.716***	0.720***
RTI x Time		0.852***	0.845***		0.939***	0.731***
Year Dummies	✓	✓	✓	✓	✓	✓
Sector x Year Dummies			✓			✓
N	1,258,912	1,258,912	1,052,440	1,052,441	1,052,441	1,052,440

Note: Control variables included in all regressions, age groups, skill groups, economic sectors, establishment size, region (Bundesland), year, regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

employment stability of 1.5 percentage points when compared to a worker who performed no routine tasks. Again, recognizing that this is an unrealistic comparison we rescale this effect by the standard deviation of RTI across our period of analysis. Doing so suggests that a one standard deviation increase in RTI was associated with a reduction in one-year employment stability of just over 10 percentage points over the past 35 years. This, we believe, is a quite dramatic reduction in employment stability. Column 3 includes industrial sector and year interaction terms. This is motivated by a concern that occupations are not distributed evenly across industrial sectors. Hence, conditional associations between RTI and employment could, at least in part, reflect sector-specific temporal shocks. In practice, this introduction does not markedly affect our estimates. The initial RTI effect moves closer to zero, but the rate of change over the period is essentially unaltered.

Columns (4) to (6) report analogous estimates for employment probability after five years, where again we include sector and year interaction terms. As column 4 shows, the probability of employment probability after 5 years is negatively affected by exposure to RTI. This average effect across the period is of a similar magnitude to that reported for employment after 1 year. Computing the marginal effect shows that workers in completely routine jobs (i.e., RTI=1) have a 6 percentage points lower likelihood of being in employment after 5 years than workers with completely non-routine jobs. Again we standardize the size of this effect. A one standard deviation increase in the RTI of a job is associated with a 1.2 percentage point reduction in being in employment after five years.

Columns (5) and (6) report estimates where again we include an interaction between RTI and time. In the case of employment probability after five years, the introduction of industrial sector and time interactions is more consequential than for the employment probability in t+1, i.e., the coefficients of interest change more when comparing specification (5) and (6) than when comparing specification (2) and (3). This is an indication that controlling for sectoral shocks matters more in the longer run (t+5) than in the short run (t+1). The estimates reported in column (6) suggest that exposure to RTI was, in the late 1970s, associated with greater employment stability over a 5 year period. However, this changed dramatically over the following 35 years, as evidenced by the interaction term between RTI and time. It is furthermore noticeable that the employment penalties associated with RTI exposure are larger for employment probability in t+5 (compare columns (3) and (6)).

Again, to aid interpretation, we re-estimated the model from column (6) as a linear probability model. These results suggest that RTI exposure was associated with a reduction of 5-year employment stability of 1.3 percentage points every year across the period. This, when again scaled by a one standard deviation increase in RTI, means that five year employment stability falls by approximately 9 percentage points across the 35 year period. Taken together, this suggests short term negative effects of RTI exposure on individual's employment stability that are exacerbated over the longer-term.

The estimates reported in Table 3.3 reflect conditional effects averaged across all workers. One question that naturally arises is the extent to which these effects are likely to be heterogeneous over different worker types. Two main dimensions likely to be particularly important are the age and skill levels of workers. Table 3.4 reports estimates that correspond to the specifications in columns (1) and (2) from Table 3.3. Hence the first column reports the average effect (across the period) of RTI exposure on employment stability, while columns (2) and (3) provide the starting (1979) effect on employment stability such that they provide the effect of RTI at the start of the period and trend effect of RTI on employment stability across the whole period. In terms of average effects, the negative effects on employment stability are concentrated among prime-age workers (26-35), with some indication that the negative effects are greater for middle-skilled workers. For all age groups RTI exposure decreases employment stability over our period of observation. There is variation in the initial effect of RTI on employment stability by skill levels. Low-skilled workers, even in 1979, faced lower employment stability if in jobs with high RTI. This RTI effect remains constant for these workers, while for both middle-skilled and high-skilled workers RTI is increasingly associated with employment instability over time.

Table 3.4: Routine Task Intensity of Current Job and Probability of Employment after 1 Year, 1979-2013, Logit Odds Ratios

	Specification 1	Specification 2	
	RTI	RTI	RTI x Time
Age			
18-25	0.91***	1.10	0.90***
26-35	0.65***	1.04	0.82***
36-45	0.62***	0.90	0.85***
46-55	0.54***	0.72***	0.89***
56-65	0.90***	1.34***	0.85***
Skill			
Low	0.78***	0.78***	0.99
Middle	0.73***	1.00	0.87
High	0.82***	1.60***	0.76***

Note: Models correspond to columns 1 and 3 in Table 3.3. Control variables included in all regressions, age groups, skill groups, economic sectors, establishment size, region (Bundesland), year fixed effects and regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

3.4.4 Task-specific Job Stability and Unemployment Exit Rates

These differences in employment probabilities by task intensity could reflect a mixture of two different factors. Specifically, task intensity could influence job stability, and/or exit rates out of unemployment. We try to disentangle these channels.

Table 3.5 provides estimates of the probability of exiting from employment to any other employment state (employed or un-employed). In this way, it provides estimates of the effect of RTI exposure on job stability. All estimates are reported as hazard ratios. We follow a similar strategy to the earlier models of employment stability by reporting models with increasingly complex specifications. The first column reports the average effect of RTI on the probability of making an employment transition. This effect is sizeable, again scaling this effect shows that a one percentage point increase in RTI leads to an approximate 0.4% increase (exp(0.34)-1) in the likelihood of exiting the current job. Recalling that the standard deviation of RTI is 0.202, this again is a large effect. Interacting this effect with time (column (2) and (3)) reveals that this risk of exit is increasing at approximately 0.04 percentage points every year, which again represents a non-negligible increase in job instability over our period of analysis.

Table 3.5: Routine Task Intensity and the Risk of Job Exit (to Employment/Unemployment), Hazard Ratios

	(1)	(2)	(3)
RTI	0.340***	0.340***	-0.190***
Time		0.002***	-0.012***
RTI x Time			0.035***
N	5,812,823	5,812,823	5,812,823

Note: Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

These overall exit rates may hide a mixture of job-to-job transitions and job-to-unemployment transitions. Welfare losses attached to technological change are most likely to be concentrated in the latter transitions. This leads us to re-estimate our duration models where instead the hazard state is exit from employment to unemployment. These results are reported in Table 3.6 and reveal more dramatic patterns of the effect of RTI exposure on job stability. RTI exposure is associated with markedly higher risk of subsequent exit to unemployment. A one percentage point higher RTI leads to an increase in the likelihood of entering unemployment of approximately 0.65%. This risk has trended up rapidly across the last 4 decades. This provides evidence that a feature of job polarization has been an increasing risk of experiencing a period of unemployment for workers performing routine tasks.

Table 3.6: Routine Task Intensity and the Risk of Exit to Unemployment, Hazard Rates

	(1)	(2)	(3)
RTI	0.498***	0.498***	-0.244***
Time		0.005***	-0.017***
RTI x Time			0.050***
N	5,433,626	5,433,626	5,433,626

Note: Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

This leads to an obvious question regarding the ability of these workers to subsequently exit unemployment and how this has changed over time. We estimate hazard models of the likelihood of exiting unemployment to employment where we use the RTI of the last employment spell as the main variable of interest. Insofar as this has any effect on re-employment probabilities this is informative of potential labor market scarring effects of RTI exposure. In practice, we find no evidence of this (Table 3.7). Previously holding an RTI-intensive job is associated, if anything, with a higher likelihood of re-entering employment, and this is trending upwards over time. This suggests that the increasing job instability of RTI-intensive work over the period has been coincident with countervailing effects on re-employment probabilities. This has the potential to have mitigated some of the welfare losses associated with this job instability and the changes in occupational structure, more generally.

The effects reported in Tables 3.5 to 3.7 are averaged across all workers. Again we seek to explore heterogeneity of effect across age groups and skill level. These results are reported in Table 3.8 grouped by the effect on risk of job exit, risk of job exit to unemployment, and subsequent likelihood (risk) of finding a job for the unemployed. For risk of job exit, and job exit to unemployment there is little evidence of variation by age, although workers in jobs with high RTI aged 26 to 35 appear to face a higher likelihood of job exit to unemployment. Differences in the effects on subsequent job finding across workers with different age and

Table 3.7: Routine Task Intensity and the Risk of Exiting Unemployment to Employment, Hazard Rates

	(1)	(2)	(3)
RTI	0.124^{***}	0.124^{***}	-0.443^{***}
Time		0.452^{***}	0.438^{***}
RTI x Time			0.032^{***}
N	2,195,087	2,195,087	2,195,087

Note: Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

education are more pronounced. RTI exposure for workers aged 36 and above is associated with an increased subsequent job finding rate. There is no effect for younger workers. Furthermore, we find evidence for strong heterogeneous effects with respect to skills, i.e., routine intensity strongly increases the unemployment exit probability of high-skilled workers. This is not apparent for low-skilled workers.

3.4.5 RTI Wage Penalties

As a final step, we provide some evidence on wage premia attached to RTI exposure, and in particular, how this has changed over our period of analysis. First, we estimate a number of models where the dependent variable is log real wages and our main right hand side variable of interest is the RTI of the job. The controls are listed in the table notes, but the coefficients are omitted for the sake of brevity. The first two columns of Table A3.1 report the relationship between current job RTI and wages. The first column provides the average wage effect of RTI across the 1975 to 2014 period, which is 0.378 log points lower. A one standard deviation increase in RTI exposure is associated with an approximate 7.6% wage penalty. The second column includes an interaction between RTI and time, such that the RTI coefficient now provides the initial wage penalty. This is -0.259, while the interaction term indicates that the RTI wage penalty increased, and quite substantially, over the period.

Table 3.8: Routine Task Intensity and the Risk of Job Exit (to Employment/Unemployment) by Age and Skill Group, Hazard Ratios

	(1) RTI: Risk of job exit	(2) RTI of job exit to unemployment	(3) RTI: Job-finding rate of unemployed
Age			
18-25	0.272***	0.327***	0.001
26-35	0.454***	0.791***	0.042
36-45	0.267***	0.383***	0.143***
46-55	0.371***	0.419***	0.216***
56-65	0.336***	0.375***	0.320***
Skill			
Low	0.336***	0.314***	-0.145***
Middle	0.298***	0.433***	0.166***
High	0.694***	1.474***	0.537***

Note: Models correspond to column 2 in Tables 3.5, 3.6 and 3.7. Control variables included in all regressions, age groups, skill groups, economic sectors (not for column 3), establishment size, region (Bundesland), year fixed effects and regional unemployment rate, constant. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

The following 4 columns provide similar results but where instead the relationship under examination is RTI of the current job and wages in the next year, or five years later, respectively. The estimates for these are very similar to those for the contemporaneous relationship between RTI and wages. Our reading of this is that there are substantial wage penalties that have increased markedly over the past four decades associated with RTI. However, there is no evidence of additional scarring effects on individual's wages due to past exposure to RTI.

Table A3.2 reports RTI exposure effects on wages by age and skill level of workers, respectively. Again, we report contemporaneous effects along with those for one year and five years on, respectively. There is a clear age gradient to the wage penalties. All age groups suffer wage penalties through RTI exposure, however the magnitude of these effects are over 3 times larger for 46 to 65 year old workers when compared to those aged 18-25. Again these effects do not change markedly over one and five year windows. A skill gradient is also apparent. High-skilled workers in jobs suffer a very large wage penalty through RTI exposure. There are substantial penalties for middle-skilled workers, and smaller effects for low-skilled workers. The high-skill RTI penalty diminishes by approximately one third over a five-year period, perhaps reflecting the greater ease with which high-skilled workers can change job. These penalties are, in contrast, quite stable for low-skilled and middle-skilled workers.

3.5 Conclusion

The past 4 decades have seen dramatic changes in the structure of the labor market. Rapid decreases in computing costs have led to a sharp reduction in the demand for jobs that are intensive in routine tasks. The existing literature highlights the aggregate patterns of labor market polarization associated with this. We revisit this issue using German administrative data that allows us to address a range of questions currently unanswered in the literature. We present, to our knowledge, the first evidence on changes in task intensity of jobs over a long period and at an annual level. This allows us to examine the trend in polarization over time which is important as the previous literature has suggested both periods of heightened polarization and/or accentuated cyclical patterns. Our first main finding is to show that neither are the case in Germany. In this context, polarization represents a steady secular change over the period of 1975 to 2014. Any cyclical patterns are dominated by this process. This is important as it suggests ongoing structural change without episodes of heightened changes in employment task shares.

With this as a starting point we seek to understand the worker transitions contributing to these patterns. Again, this is an analysis for which our data is particular well suited and where there is little existing evidence. Our results suggest that exposure to jobs with higher routine-task content is associated with higher risk of being out of employment in both the short term (after 1 year) and medium term (5 years). Subsequent results show that this employment penalty to routineness of work has increased over the past four decades.

The reasons for the employment penalty to routineness of work were then traced back to routine task work being associated with reduced job stability and an associated higher likelihood of making a transition to unemployment and thus experiencing periods of unemployment. By contrast, we find that previous work with high RTI for unemployed persons is associated with higher job-finding rates out of unemployment, which thus at least partly compensates for the negative effects of RTI on employment stability.

A3 Appendix

Table A3.1: Wages at Different Time Horizons and RTI, Coefficients from OLS Regression

	t=0		t=1		t=5	
	(1)	(2)	(3)	(4)	(5)	(6)
RTI	-0.378***	-0.259***	-0.382***	-0.267***	-0.368***	-0.287***
Time	0.012***	0.032***	0.008***	0.027***	-0.006***	0.010***
RTI x Time		-0.052***		-0.050***		-0.041***

Source: SIAB 1975-2014, BIBB/BAuA/IAB survey, own computation. Dependent variable: log wages. RTI refers to time 0 in all regressions. Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5%and 10% level respectively.

Table A3.2: Wages at Different Time Horizons and RTI by Age and Skill Group, Coefficients from OLS Regression

	t=0	t=1	t=5
	(1)	(2)	(3)
Age			
18-25	-0.141***	-0.123***	-0.134***
26-35	-0.304***	-0.303***	-0.308 ***
36-45	-0.455***	-0.441***	-0.398***
46-55	-0.523***	-0.514***	-0.446***
56-65	-0.535***	-0.535***	-0.501***
Skill			
Low	-0.114***	-0.097***	-0.116***
Middle	-0.440***	-0.433***	-0.383***
High	-0.600***	-0.577***	-0.401***

Source: SIAB 1975-2014, BIBB/BAuA/IAB survey, own computation. Dependent variable: log wages. RTI refers to time 0 in all regressions. Control variables included in all regressions: Duration dummies: 0 "0 - 3 months", 1 "4 - 12 months", 2 "1 - 2 years", 3 "2 - 5 years", 4 "5 - 10 years", 5 "> 10 years"; Age groups, skill groups, economic sectors, establishment size, region (Bundesland), regional unemployment rate, year dummies. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level respectively.

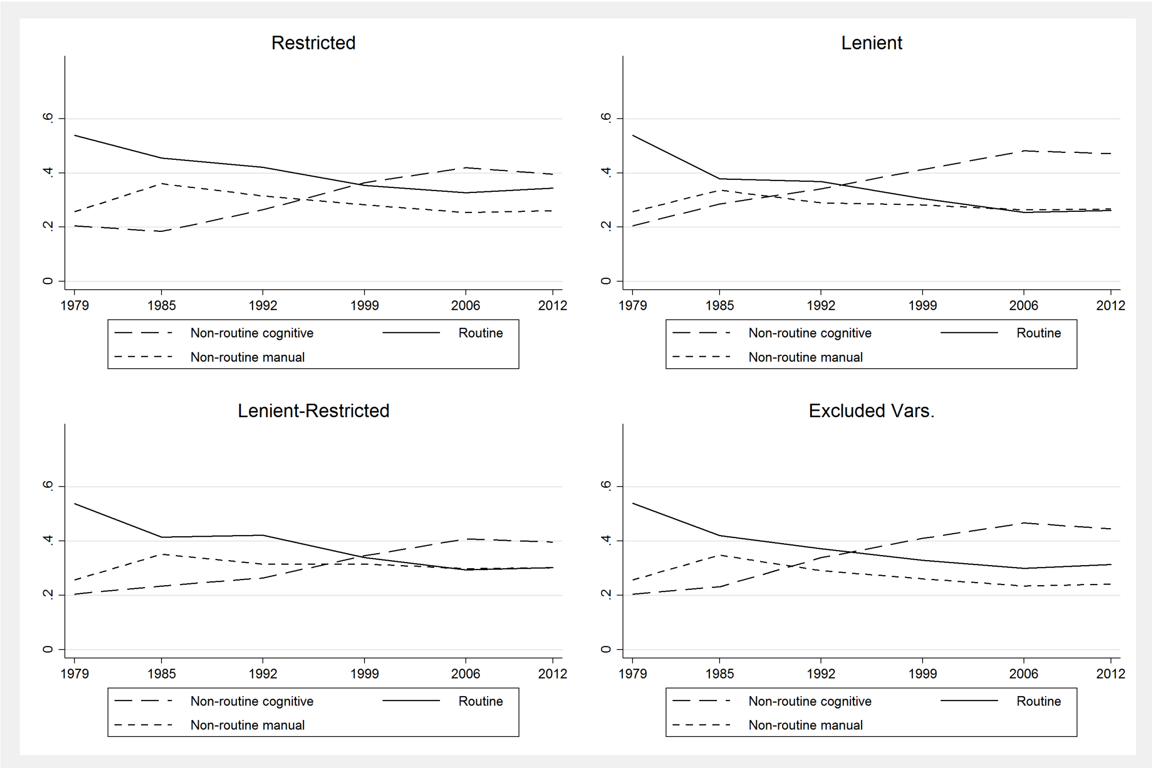
A3.1 The BIBB Data and Computation of Task Intensity Measures

The first four waves of the task data were conducted under the name "Qualification and Career Survey" in a collaboration of German Federal Institute for Vocational Education and Training (Bundesinstitut für Berufsbildung: BIBB) and the Institute for Employment Research (Institut für Arbeitsmarkt- und Berufsforschung: IAB). The 2006 and 2012 waves were conducted as "BIBB/BAuA Labor Force Survey", which were jointly carried out by BIBB and the Federal Institute for Occupational Safety and Health (Bundesanstalt für Arbeitsschutz und Arbeitsmedizin: BAuA).

In the cross-section BIBB surveys, workers state which activities they perform at their workplace from a given list. Although the surveys include a rich set of workplace activities, the number and the definition of the surveyed activities differ across waves. While the 1979 wave covers approximately 90 activities, the number of activities decreased to 19 in the 2012 wave. In order to create a task intensity measure that is consistent over time, we excluded the activities that appeared only in one wave. We merged some of the activities into one variable in order to deal with the changing definitions of the variables and to maintain a total number of activities which is similar in each survey. For example, the activity "buying, selling, advertising" in the 1985 wave was split into two separate variables as "buying and selling" and "advertising" in 1999; we thus merged these two variables to make the comparison to the previous wave easier. The answer categories in the surveys were also different across waves. While in some waves the answer category was binary, in other waves workers were asked whether they performed an activity "often", "sometimes", or "never". In case of three-category answers, we classified the answer categories "sometimes" and "never" together to have a consistent binary variable.

We tested the robustness of our results by applying four alternative definitions of task intensity measures to deal with the inconsistencies across waves mentioned above. In the "restricted" approach, we merge even more survey questions compared to the baseline approach in order to keep the number of questions in all three task categories as close to each other as possible. The "lenient" definition assumes that an activity is applied when the answer to survey questions is "always" or "sometimes" whereas the baseline category uses only the answer category "always". "Lenient-Restricted" approach applies the lenient definition to the restricted set of merged variables. Finally the "excluded variables" definition ignores the survey questions which were not repeated in all the waves. The results of these robustness analyses are available from the authors upon request.

Figure A3.1: Average Task Intensities of Employment from the BIBB Data, Different Measures



4 Immigration and Task Specialization of Natives: Evidence from Germany

Abstract. This study examines whether natives in Germany respond to immigration by increasing their supply of communication tasks as they have a comparative advantage in communication skills. The empirical results support the hypothesis of specialization in communication tasks in the regions with a higher share of foreign workers. Results of different instrumental variable approaches reinforce the finding of significant task specialization of natives. The paper further analyzes the role of occupational mobility on task changes. More specifically, the change in the task supply of natives is decomposed into the change arising from a reallocation of natives into more communication intense occupations and the change due to altering skill requirements within occupations over time. The results indicate that a major part of the overall task change arises from changes in skill requirements within occupation.

4.1 Introduction

Contrary to the common public belief that immigrants take away jobs from natives and cause lower wages, the existing empirical evidence indicates very small to null effect of migration on the employment level and wages of natives in Germany (e.g., Bauer, Flake, & Sinning, 2013; Bonin, 2005; D'Amuri, Ottaviano, & Peri, 2010). Little is yet known about the adjustment mechanisms of labor markets which lead to those findings.

The effect of immigration on the labor market outcomes of natives depends on the degree of substitution between natives and immigrants. Economic theory predicts negative effects for natives with a similar educational level to immigrants. However, if natives with similar levels of education to immigrants differ in their skill endowments, they are likely to perform different tasks and different occupations. Ottaviano and Peri (2012) argue that natives and immigrants are not perfect substitutes and that they do not compete for the same jobs, which is the driving factor behind the null or small effect of immigration on natives. Peri and Sparber (2009) discuss in a similar manner that natives and immigrants differ with respect to their skills, especially language skills, and this difference causes them to be allocated unevenly across occupations. Due to their more advanced language skills, natives have a comparative advantage in performing occupations which involve communication tasks, whereas immigrants are more likely to be represented in occupations that require relatively more manual tasks. By exploiting US data, Peri and Sparber (2009) find that immigrant inflows push natives into more communication intense occupations and therefore there is no significant employment effect of immigration on natives.

The comparative advantage model proposed by Peri and Sparber (2009) has been applied to other countries, e.g., Spain (Amuedo-Dorantes & de la Rica, 2011) and the United Kingdom (Bisello, 2014), and qualitatively similar findings are reported. Based on the same empirical approach, this paper provides evidence on the task specialization hypothesis in the German labor market, which could serve as a potential mechanism behind the observed small labor market effects of immigration in Germany.

Analyzing the German evidence is of importance due to the different structure of the German labor market compared to the US. The German labor market can be described as relatively rigid, which hinders occupational mobility. In a cross-country analysis, D'Amuri and Peri (2014) find that natives in countries with more flexible labor laws experience a job switch into more complex and communicative tasks to a greater extent. Thus, flexible labor markets can adjust to immigrant inflows more easily by occupational mobility of natives. Therefore, it is interesting to study the German case of natives' task specialization and compare the results to those from the US where, due to labor market flexibility, natives can respond to labor supply shocks more easily.

This paper contributes to the literature by exploiting a unique data source on the task content of occupations to provide evidence on the task supply response of natives to immigration in Germany. In contrast to other European studies, which rely on information from the US Department of Labor's O*NET data for measuring workplace task requirements and assume that local workplace task requirements are identical to the requirements in the US labor market, the current study uses country-specific task measures, which are estimated using individual level surveys representative for the German labor force. Moreover, earlier studies focus on natives' task supply change, which results from occupational reallocation of natives, ignoring that task requirements within occupations may change over time. As the task surveys, which the current paper relies on, are repeated approximately every 6 years, it is possible to account for changes in the workplace tasks within occupations over time. Against this background, the changes in the aggregate task supply of natives are decomposed into two components: *between change*, which arises from mobility of natives into more communication intense occupations, and *within change*, which arises from changing task requirements within occupations over time.

The results show that natives in Germany respond to immigration by altering their task supply. In regions with higher foreign shares, natives perform more communication tasks. This relationship is indicated by OLS results as well as two different instrumental variable approaches. However, the size of the effect depends on the choice of the instrument. Some of the heterogeneous effects, i.e., with respect to age and skill level, among the native population are also highlighted in the paper. Younger and middle-skilled workers respond to immigration by altering their task supply, whereas no such effect is observed for the older and low-skilled workers. Finally, a remarkable part of the overall task change is shown to arise from changing task requirements within occupation over time rather than through occupational mobility.

The paper is structured as follows. Section 4.2 gives an overview of the studies examining the labor market effects of immigration on natives and briefly summarizes the task-based approach applied in the literature in this context. Section 4.3 explains the econometric specification and introduces the two data sources, which are used in the analysis. Section 4.4 presents estimation results and Section 4.5 contains concluding remarks.

4.2 Related Literature

There is a large body of literature investigating the labor market effect of immigration on natives. The effect largely depends on the estimation model and its related assumptions on the substitutability between immigrants and natives. While earlier studies find varying results for the US, empirical literature has a consensus that immigration does not have a significant negative impact on the labor market outcomes of natives in Germany (e.g., Bauer et al., 2013; Bonin, 2005).

One of the most commonly applied approaches in the migration literature is the education-experience cell approach proposed by Borjas (2003). By assuming that immigrants and natives within the same education-experience cell are comparable, he exploits the variation in the migrant share across the education-experience groups and finds negative effects of migration on the native wage outcomes in the US. Applying the same method for Germany, both Bonin (2005) and Steinhardt (2011) find no adverse effect of immigrants in Germany. However, Steinhardt (2011) finds that immigrants and natives with similar education and experience work in different occupational segments. Thus, immigrants and natives within the same education-experience cell are not close substitutes in Germany. His results suggest that in the German labor market, which is characterized by occupational segmentation, using formal education as classification unit leads to an underestimation of the effect of immigration. Accounting for the occupational sorting of immigrants, he finds adverse wage effect for natives, but this effect is rather small.

Peri and Sparber (2009) also claim that migrants and natives do not compete for the same occupations. Contrary to Borjas (2003), who analyzes the labor market at national scope, they follow a spatial analysis approach with the assumption of closed local labor markets. Their seminal contribution is to incorporate the task content of occupations, by looking beyond the formal qualifications of workers, to study a potential adjustment mechanism of the labor market to immigration. Considering the task content of occupations sheds more light on the substitution between natives and immigrants and allows to understand the mechanisms leading to small labor market effects of immigration on natives. They suggest that even within the same education group, natives and immigrants can differ in terms of their skills, especially language skills. Thus, they work in occupations which require different types of tasks. For example, natives more frequently perform communication tasks while immigrants are more frequently represented in manual jobs. The results of Peri and Sparber (2009) indicate a displacement effect of immigration on natives from manual towards communication tasks in the US.

Applying a similar task-based approach, Amuedo-Dorantes and de la Rica (2011) also find a positive effect of immigration on natives' communication task supply in Spain, which is twice as large as in the US. They distinct between native and non-native speaker immigrants and show that native speaker immigrants have a lower manual to communication task supply ratio compared to non-native speaker immigrants. Moreover, the impact of non-native speaker immigrants on the task specialization of natives is larger compared to the impact of native speaker immigrants on natives as native speaker immigrants can compete better with natives also for the communication tasks. These results with the distinction between native and non-native speaker immigrants provide a further and stronger evidence that differences in the language ability drive the task supply differentials and support the comparative advantage hypothesis.

Foged and Peri (2016) provide new causal evidence by analyzing variation in the share of refugees in Denmark, who are allocated into regions randomly by a refugee dispersal policy. Different from the studies of Peri and Sparber (2009) and Amuedo-Dorantes and de la Rica (2011), which rely on instrumental variable approach to deal with endogenous allocation of immigrants into regions, the identification strategy of Foged and Peri (2016) is based on an exogenous variation. Their findings also indicate a significant communication task specialization of natives as a response to refugee inflow. They state that specialization of natives in communication tasks leads to positive effects on their wages, employment, and occupational mobility.

The above mentioned studies, which provide evidence on the task response of natives, fail to account for changing workplace tasks within occupations. A drawback of relying on the O*NET data, which is based on experts' assessment, is that it is not updated very frequently to adjust for changing task requirements of occupations. Therefore, these studies are likely to underestimate the effect of immigration on the task performance of natives as they only capture the task changes due to reallocation of natives across occupations.

Analyzing the overall changes in the workplace tasks in the German labor market, Spitz-Oener (2006) finds that task changes arising from changing task requirements within occupations over time is substantially more important than task changes arising from occupational mobility. She shows that 13% (14%) of the interactive (manual) task change arose from between shift and 87% (86%) from within change between 1979 and 1999. Thus, it is important to account for the changing task requirements to evaluate the impact of immigration on natives more accurately.

4.3 Methodology and Data

4.3.1 Empirical Specification

This paper exploits the Peri and Sparber (2009) model of comparative advantage in performing communication and manual tasks among low-skilled workers. The model is based on the assumption that low-skilled natives have a comparative advantage in communication tasks due to their language proficiency. It is important to note that this comparative advantage model, which considers the relative performance in only communication and manual tasks, applies only to low-skilled workers since the task requirements of high-skilled occupations differ from the low-skilled ones. While manual tasks compose a substantial part of low-skilled occupations, high-skilled occupations are mostly formed by communication and analytical/cognitive tasks and they involve a negligible amount of manual tasks. To avoid the incomparability between the skill and the task requirements of the high-skilled and low-skilled occupations, the model assumes that high-skilled workers perform only analytical/cognitive skills and focuses on the low-skilled workers, who divide their work between communication and manual tasks.[1]

The theoretical model assumes that low-skilled native and foreign workers differ from each other in their task productivity. They allocate their working time between these two tasks to maximize their labor income. The workers change their occupation if the relative compensation of tasks changes. This implies, when the relative compensation of communication tasks increases, they move to an occupation requiring less time on manual tasks and thus increase their relative supply of communication tasks. Therefore, an increase in the share of foreign workers leads to a higher relative communication task supply of natives. For a detailed description of the theoretical model, see Peri and Sparber (2009).

The empirical model uses the spatial correlation approach by estimating the change in the communication task intensity of low-skilled natives (C^N) relative to their manual task intensity (M^N) in each labor market region, r, in year, t. The empirical model is:

$$ln\left(\frac{C^N}{M^N}\right)_{r,t} = \alpha_r + \tau_t + \gamma \mathrm{f}_{r,t} + \epsilon_{r,t} \tag{4.1}$$

where f is the foreign share in region r at time t and α_r and τ_t are region fixed effects (accounting for region-specific unobserved characteristics) and time fixed effects (accounting for common time-varying technological parameters such as nationwide technological shocks), respectively. Equation (4.1) is estimated using ordinary least squares and clustering the standard errors at the regional level.

Before estimating regional averages, I clean the task data of demographic effects to account for the spurious correlation between the foreign population and the task supply of natives. This is done by regressing each individual's task supply on education and age to compute

[1]A more recent study by Peri and Sparber (2011) empirically shows that high-skilled immigrants have a comparative advantage in cognitive tasks and perform jobs that are intense in cognitive skills such as engineers, medical scientists and software developers, whereas high-skilled natives have a comparative advantage in communication tasks and are presented more frequently in occupations like financial managers or sales & purchasing agents.

the predicted task supply. The predicted task supply is then subtracted from the individual's observed task supply to get the residuals cleaned of individual characteristics. These residuals are used to estimate regional averages, which are employed in the estimation of Equation (4.1).[2]

In addition to the relative task intensity, Equation (4.1) is also estimated separately for the communication (C^N) and manual (M^N) tasks to examine whether immigration has a stronger effect on the manual or with the communication task supply of natives:

$$ln(C^N)_{r,t} = \alpha_r^C + \tau_t^C + \gamma^C \mathrm{f}_{r,t} + \epsilon_{r,t}^C \tag{4.2}$$

$$ln(M^N)_{r,t} = \alpha_r^M + \tau_t^M + \gamma^M \mathrm{f}_{r,t} + \epsilon_{r,t}^M \tag{4.3}$$

The empirical model assumes that labor markets are local and natives do not move across regions as a response to immigration. Out-migration of natives would affect the measurement of immigrants' impact on the local labor market. Using German data, Pischke and Velling (1997) find no regional displacement effect of immigration for natives. Moreover, Lehmer and Möller (2008) show that the regional mobility among low-skilled workers is very low in Germany. Therefore, the results in this paper are not likely to be driven by the regional mobility response of natives.

A further assumption for estimating the true impact of immigration on natives is that the share of immigrants is accurately measured. Most studies in the literature rely on small-size surveys and thus additionally use census data or national statistics to deal with potential measurement error. This is not a relevant concern for this paper as it relies on a large-scale administrative data set.

Potential endogeneity of migrants' location choice indicates a more relevant issue for the identification. Immigrants are not randomly allocated into local labor markets and their location decision might be influenced by the same labor demand conditions that could simultaneously impact the task supply of natives. This issue is addressed by using a shift-

[2]The results from this step are not reported but are available upon request.

share supply instrument based on the paper by Card (2001), which uses the past settlement of immigrants to remove unobserved demand shocks that could impact the location choices of immigrants. Relying on past settlements is especially relevant for low-skilled workers as ethnic networks play an important role in their location decision (Bartel, 1989). Assuming that current economic shocks are independent of the past settlement of immigrants, the shift-share instrument gives an exogenous measure of the foreign population share.

To construct the instrument, the population level of foreigners by their origin in a base year (1985) is calculated. Immigrants are clustered into 4 groups based on their origin: Turkey, guest-worker countries (i.e., Italy, Spain, Portugal, Greece and former Yugoslavia; excluding Turkey)[3], EU countries (excluding the guest-worker countries), and non-EU countries. The population levels from the base year are then multiplied by the national population growth rate of each origin group. The imputed numbers of foreigners for each origin group are aggregated at the region-year level. Finally, the total number of the imputed foreign population is divided by the total population within each cell. The procedure can formally be shown as:

$$\hat{f}_{r,t} = \frac{\sum_{i=1}^{4} f_{o,r,1985} * (1 + g_{o,1985-t})}{native_{r,t} + \sum_{i=1}^{4} f_{o,r,1985} * (1 + g_{o,1985-t})} \tag{4.4}$$

where $f_{o,r,1985}$ is the foreign share from origin country, o, in region, r, in the base year and $(1 + g_{o,1985-t})$ is the overall growth rate of foreigners by origin country, o, between 1985 and year t.

Despite its widespread application in the literature, this instrumental approach has recently been criticized by Clemens and Hunt (2017) for the reason that both the instrument and the endogenous variable have a common divisor, since the size of the native population in each region changes only very little over time. They argue that this can generate spurious correlation between the ratios of the foreign and the lagged foreign population regardless of the change in the numerator (i.e., the foreign population). Thus, they suggest a specification

[3] Although Turkey is also a guest-worker country, it is taken as a separate group as Turkish immigrants represent the largest ethnic group in Germany.

correction for the instrumental variable which was proposed initially by Kronmal (1993) in an ordinary least squares setting:

$$ln\left(\frac{C^N}{M^N}\right)_{r,t} = \alpha_r + \tau_t + \gamma \text{asinh} Foreign_{r,t1} + \gamma' \text{asinh} Native_{r,t1} + \epsilon_{r,t} \tag{4.5}$$

where *asinh* is the inverse hyperbolic sine. $Foreign_{r,t1}$ and $Native_{r,t1}$ are the stock of foreign and native population, respectively. The endogenous immigrant supply stock (asinh $\text{Foreign}_{r,t1}$) is instrumented by the predetermined stock of prior immigrants (asinh $\text{Foreign}_{r,t0}$). The current paper applies this correction approach and compares the results with those obtained by using the shift-share instrument.

4.3.2 Decomposing Task Intensity Change

Changes in the aggregate task supply may arise from two different channels: a change in task requirements within the same occupation over time and a change in the occupational distribution. Thus, an increase in natives' supply of communication tasks could represent an occupational shift towards more communication intensive jobs (i.e., between occupation change) or it can be due to an initial over-representation of natives in occupations in which communication tasks became more important over time (i.e., within occupation change).

In order to disentangle the task changes arising from occupational mobility and changing task requirements within the occupation, natives' task change is decomposed into two components following the task decomposition applied by Spitz-Oener (2006):

$$\Delta \text{T}_{j,t} = \underbrace{\sum\nolimits_{occ} (\Delta \text{E}_{occ,t} \overline{\rho}_{occ,j})}_{\Delta \text{T}_{j,t}^{\text{between}}} + \underbrace{\sum\nolimits_{occ} (\Delta \rho_{occ,j} \overline{\text{E}}_{occ,t})}_{\Delta \text{T}_{j,t}^{\text{within}}} \tag{4.6}$$

where j is the type of task (C, M), $E_{occ,t}$ is the share of employment in occupation (occ) in total employment, $\rho_{occ,j}$ is the intensity of task j in occupation occ, $\overline{\rho}_{occ,j}$ and $\overline{E}_{occ,t}$ are the average task intensity and employment share within each occupation over time, respectively.

4.3.3 Data

The data applied in this paper come from two different sources. Task intensity measures of the occupations are estimated by exploiting the Qualification and Career Survey conducted by the German Federal Institute for Vocational Training (BIBB) in cooperation with the Research Institute of the Federal Employment Service (IAB) and the Labor Force Survey of BIBB and Federal Institute for Occupational Safety and Health (BAuA). These surveys take place in approximately 6-year frequency. This paper employs the last three waves of the surveys, i.e., 1998/1999, 2006 and 2012. In the surveys, employees are asked which activities they perform at their workplace. Using the information on the performed tasks, individual task intensity measures are calculated based on the method suggested by Antonczyk et al. (2009) using the same data. A detailed description of the surveys and the calculation of the task intensity measures are provided in Chapter 3.

Table 4.1: Assignment of Activities into Tasks

Task Category	Workplace activity
Communication	Negotiating, lobbying; coordinating, organizing; teaching or training; selling, buying, advising customers; advertising; entertaining or presenting; employing or managing personnel
Manual	Operating or controlling machines and equipping machines; repairing or renovating houses, apartments, machines, vehicles; restoring art, monuments; and serving or accommodating

The categorization of tasks in this paper differs slightly from Chapter 3. Tasks are divided here into 3 categories: communication, manual and cognitive/analytical. The intensity measure of each task represents the relative importance of that task among all the tasks an individual performs. As the theoretical model is based on the comparative advantage in communication tasks relative to manual tasks, the current paper focuses only on communication and manual tasks and omits cognitive/analytical tasks.[4]

Communication tasks consist of activities which require advanced language skills, such as negotiating, teaching, presenting, while manual tasks are described as those with less in-

[4]As cognitive tasks represent only a very small part of low-skilled occupations, ignoring those tasks does not imply a problem for this analysis. See Section 4.3.1 for the discussion on task categories. As a robustness test, I examine the change in the cognitive task supply of natives and find no significant effect.

tense language skill requirements. Table 4.1 presents a list of assignment of activities to task categories. Table 4.2 displays the occupations with the highest and lowest relative (communication/manual) task intensity with the related task intensity measures at the beginning and end of the estimation period.

Table 4.2: Occupations with the Highest and Lowest Communicative (C) vs Manual (M) Task Intensity Ratio

Occupation	C	M
1999		
Occupations with highest C/M :		
Occupations in finance and accounting	0.63	0.10
Technical draughtsman	0.50	0.12
Administrative occupations in the public sector	0.59	0.15
Legal occupations	0.60	0.16
Commercial office occupations	0.65	0.18
Occupations with lowest C/M :		
Transport occupations	0.11	0.85
Occupations in spinning and rope-making	0.08	0.69
Metal productions and processing	0.07	0.73
Occupations in production and processing of glass and ceramic	0.07	0.78
Laborers	0.06	0.76
2014		
Occupations with highest C/M :		
Advertising specialists	0.60	0.05
Legal occupations	0.49	0.07
Occupations in insurance and financial services	0.56	0.09
Journalists, librarians, translators, academic occupations	0.41	0.09
Managing directors, auditors, consultants	0.55	0.12
Occupations with lowest C/M :		
Cleaning and disposal occupations	0.12	0.81
Laborers	0.10	0.71
Metal productions and processing	0.08	0.61
Miners and mineral extraction workers	0.09	0.76
Occupations in plastic and chemistry processing	0.07	0.66

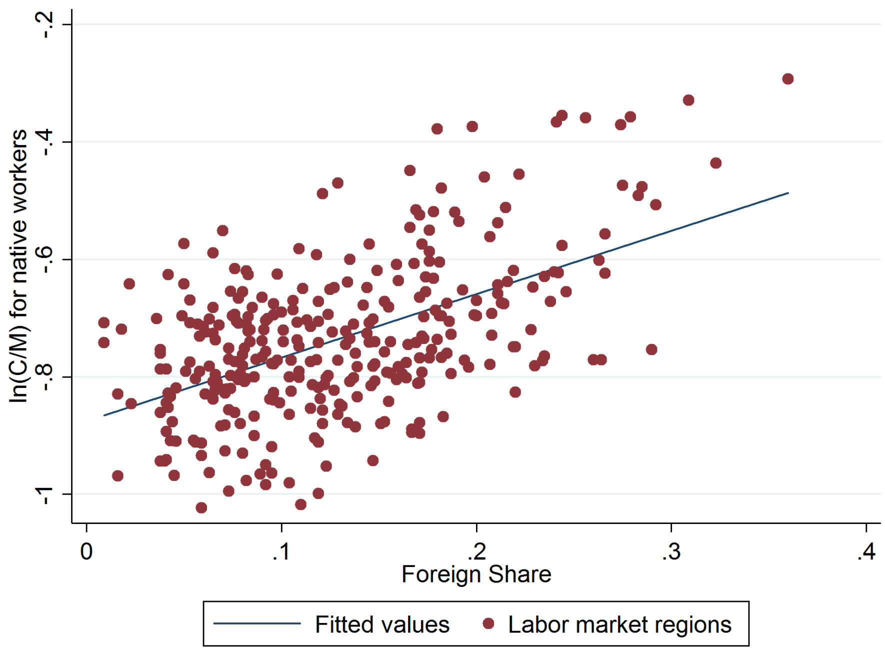
Source: BIBB/BAuA/IAB Surveys

The individual level task intensity measures calculated from the BIBB surveys are aggregated at the occupational level and then mapped to the Sample of Integrated Labor Market

Biographies (SIAB) using occupational codes.[5] SIAB is a 2 percent random sample drawn from the Integrated Employment Biographies (IEB) and is representative for the labor force. A detailed description of the data can be found in the data report by Antoni, Ganzer, and vom Berge (2016). This paper covers the time period 1999 to 2014.[6]

Due to the model specification, only low-skilled and middle-skilled workers are considered and all high-skilled individuals, i.e., those with a university degree, are excluded. The analysis considers only men as the labor market responses of women differ significantly from men. The sample includes individuals aged between 18 and 65.

Figure 4.1: Share of Immigrants and the Relative Task Supply of Natives



Source: SIAB, years 1999, 2006 and 2014.

As the share of foreigners living in East Germany is very low and remained very stable over time, the focus of the paper is only on West Germany. The unit of the econometric analysis

[5]This study uses the weakly anonymous Sample of Integrated Labor Market Biographies (1975-2014). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

[6]The task intensity measures do not change on a yearly basis at the occupational level as the BIBB/BAuA/IAB surveys are repeated by approximately 6 year frequency. Therefore, task intensities for the years between two surveys are interpolated from the last available survey. Yearly changes in aggregate task measures at the regional level between two survey years come from the change in the occupational distribution within region.

are labor market regions. In West Germany, there are 108 labor market regions. The SIAB data contain information on citizenship but not on the place of birth. Therefore, immigrants are identified by citizenship. Throughout this paper, the term immigrants refers to foreign workers.

The relationship between the relative task intensity of natives and the share of low-skilled immigrants is displayed by Figure 4.1. There is a strong positive correlation between the relative task supply of natives and the foreign share, which provides a preliminary evidence that a higher share of immigrant population leads natives to supply more communication tasks relative to manual tasks.

4.4 Results

4.4.1 Task Supply Response of Natives

Columns (1) and (2) of Table 4.3 report the OLS results for three outcome variables, i.e., the relative and the two absolute task intensities. The results support the hypothesis of an increasing relative task supply of natives as a response to immigration. The significant coefficient of 0.605 implies that a 1 percentage-point increase in the foreign-born share of low-skilled workers is associated with a 0.605 percent increase in the relative supply of communication versus manual tasks among natives.

The results for the absolute task intensity changes show that the change in the relative task intensity arises from both an increase in the communication task supply and a decrease in the manual task supply. This result is not surprising as the task intensity measures represent shares of each category, and therefore an increase in one category is likely to result in a decrease in the other category. The higher coefficient of communication tasks (0.345) compared to manual tasks (-0.261) nevertheless implies that the relative task increase is more strongly associated with communication tasks.

In order to demonstrate that the OLS results indicate a causal effect rather than a correlation, columns (3) and (4) of Table 4.3 present the two-stage least squares results employing the shift-share instrument of imputed foreign share. Accounting for potential endogeneity

Table 4.3: Share of Low-Skill Foreign Workers and Natives' Task Supply

	OLS		2SLS	
Independent Variable: Foreign Share	(1)	(2)	(3)	(4)
Dependent Variables:				
$ln(C/M)$	1.382***	0.605**	1.703***	1.048**
	(0.289)	(0.195)	(0.320)	(0.526)
$ln(C)$	0.782***	0.345*	0.996***	0.634*
	(0.192)	(0.138)	(0.213)	(0.372)
$ln(M)$	-0.600***	-0.261***	-0.707***	-0.413**
	(0.099)	(0.069)	(0.110)	(0.173)
Year fixed effects	✓	✓	✓	✓
Region fixed effects		✓		✓
N	1,728	1,728	1,728	1,728
Kleibergen-Paap F			746	29.409

Note: The table reports the foreign share coefficient obtained from separate regressions for three different outcome variables presented in each row. Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1. Estimations are based on SIAB(1999-2014).

of immigrants' regional placement leads to a stronger specialization effect. Natives increase their supply of communication task intensity by 0.634 percent for a 1 percentage-point increase in the foreign employment share and decrease their manual task intensity by 0.413 percent, resulting in a net increase of 1.048 percent in the relative task supply.

4.4.2 Source of the Task Change

This section analyzes potential mechanisms behind changes in the task supply of natives. First, demand-side changes, which could drive the increasing relative supply of communication tasks, are taken into consideration. Over the last decades, certain sectors gained more importance as a result of the technological change and the differences in the sectoral distribution within regions could drive changes in the communication and the manual task demand of the regions over this period. In order to account for sector-driven task demand changes, I follow the approach of Peri and Sparber (2009) and create a region-specific index of relative task demand based on the past industrial composition of each region assuming that occupational composition of industries and industry-specific employment shocks are uniform across regions.[7] Table 4.4 reveals that incorporating the sector-driven task demand variable into the specification reduces the size of the coefficients slightly. However, there is still a strong significant effect which implies that only a small part of the task supply change was driven by sectoral differences between regions and the associated task requirements of the sectors.

Table 4.4: Natives' Task Supply: Accounting for Sector-Driven Task Demand

	OLS		2SLS	
Independent Variable: Foreign Share	(1)	(2)	(3)	(4)
Dependent Variables:				
$ln(C/M)$	0.605**	0.491**	1.048**	1.015**
	(0.195)	(0.171)	(0.526)	(0.499)
$ln(C)$	0.345*	0.255*	0.634*	0.608*
	(0.138)	(0.117)	(0.372)	(0.347)
$ln(M)$	-0.261 ***	-0.236***	-0.413**	-0.406**
	(0.069)	(0.066)	(0.173)	(0.170)
Sector-Driven Task Demand		✓		✓
Year fixed effects	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓
N	1,728	1,728	1,728	1,728
Kleibergen-Paap F			29.409	29.284

Note: The table reports the foreign share coefficient obtained from separate regressions for three different outcome variables presented in each row. Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1. Estimations are based on SIAB(1999-2014).

Second, the effect of distributional changes across occupations (between occupation change) is disentangled from changing task requirements of the occupations over time (within occupation change). Estimation of Equation (4.6) states that only about one third of the communication task change is due to occupational mobility whereas the rest of the changes come from the changing task requirements of the occupations over time. This picture is more severe for the manual tasks. Only less than 5% of the overall change in manual task intensity is due to occupational mobility.

Lastly, I restrict the sample to individuals who experienced an occupational change and estimate their task supply response. While the OLS results in Table 4.5 do not show a significant effect, the IV results indicate a significant positive effect on the relative task

[7] See appendix for the estimation of the index.

intensity of natives. Disentangling the relative task intensity shows that this positive effect is mainly driven by increasing communication tasks rather than a change in manual tasks. Those who change the occupation experience a stronger and significant increase in the communication task supply. This finding supports previous decomposition results showing that between-occupation change was more distinct in communication tasks compared to manual tasks.

Table 4.5: Task Supply of Natives with Occupational Mobility

Independent Variable: Foreign Share	(OLS)	(2SLS)
Dependent Variables:		
$ln(C/M)$	0.556	1.283*
	(0.343)	(0.764)
$ln(C)$	0.312	0.879*
	(0.222)	(0.515)
$ln(M)$	-0.244	-0.403
	(0.129)	(0.280)
Year fixed effects	✓	✓
Region fixed effects	✓	✓
N	1,728	1,728
Kleibergen-Paap F		29.409

Note: The table reports the foreign share coefficient obtained from separate regressions for three different outcome variables presented in each row. Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1. Estimations are based on SIAB(1999-2014).

4.4.3 Robustness Analysis

In this section, the robustness of the earlier results to the choice of instrumental variable is tested. Due to the previously mentioned common regressor problem of the shift-share instrument, I apply the Kronmal correction. The results of this correction are shown in Table 4.6. After applying the Kronmal correction, there is still a significant task specialization effect. This effect is, however, lower than the effect obtained from shift-share instrument. The Kronmal correction leads to an approximately 0.50 [8] percentage increase in the relative

[8] This measure is obtained by multiplying the Kronmal coefficient by (1-m)/m where m is the immigrant share. As the share of foreign-born workers is about 9% on average in the sample, the estimation of the effect follows as: 0.048*(1-0.09)/0.09=0.485.

task supply of natives. Despite the difference in the magnitude of the effect, both instrumental variable approaches suggest that natives respond to immigration by increasing their relative communication task supply. Results for the absolute task intensity changes are also qualitatively in line with the results of the shift-share instrument. The relative task change is strongly associated with both an increase in natives' supply of communication tasks and a decrease in manual tasks.

Table 4.6: Natives' Task Supply: Alternative IV Approach

	$ln(C/M)$	$ln(C)$	$ln(M)$
asinh foreign population	0.048***	0.023*	-0.025***
	(0.018)	(0.012)	(0.006)
asinh total population	0.018	0.021	0.003
	(0.024)	(0.017)	(0.007)
Year fixed effects	✓	✓	✓
N	1,728	1,728	1,728
Kleibergen-Paap F	630.217	630.217	630.217

Note: *asinh* is inverse hyperbolic sine. Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1.

Additional robustness checks are applied for the estimation of the foreign share. In the empirical analysis, the foreign share refers to the share of low-skilled foreigners in low-skilled employment. However, as the high overeducation rates among immigrants indicate, also high-skilled immigrants can be employed in low-skilled occupations.[9] Therefore, I include also the high-skilled immigrants in the sample while estimating the share of immigrants. This leads to a qualitatively similar result with slightly lower coefficients.[10]

Lastly, I restrict the definition of foreign workers only to recent immigrants, i.e., those with less than 5 years of work experience in Germany. As recent immigrants have lower language skills, they could have a stronger displacement effect on natives from manual towards communication tasks. Therefore, I take the share of the recent immigrants as explanatory variable. The effect becomes larger.[11] Additionally, I examine the effect of recent immigrants on the immigrants with more than 5 years of work experience in Germany and

[9] See Chapter 2 for an overview of overeducation among immigrants.
[10] The result is reported in column (1) of Table A4.1 in the appendix.
[11] See column (2) of Table A4.1 in the appendix.

find no significant effect. Even after long years of experience in the German labor market, immigrants do not switch to occupations with higher communication requirements.[12]

4.4.4 Heterogeneous Effects

This section examines the relative task supply of different subgroups in the native population. Due to different individual characteristics and skill endowments of the subgroups, their labor market response could differ drastically. Therefore, the sample is divided into subgroups with respect to age and skill level and their task supply adjustments to immigration are estimated separately.

First, the effect on young workers, i.e., those younger than 40, is examined. Younger workers are expected to be occupationally more mobile than older workers. Moreover, the skill sets of different cohorts can be different, which could allow them to perform different tasks. Thus, the task supply response of younger workers is expected to be larger than older workers. Table 4.7 shows that earlier results are mainly driven by young workers. Older workers do not alter their relative task supply as a response to immigration.

Table 4.7: Natives' Relative Task Supply: IV Results with Heterogeneous Effects

Independent Variable: Foreign share	Young	Old	Middle-Skilled	Low-Skilled
Dependent Variable:				
$ln(C/M)$	1.112*	1.039	1.0381*	1.329
	(0.597)	(0.671)	(0.543)	(1.165)
Year fixed effects	✓	✓	✓	✓
Region fixed effects	✓	✓	✓	✓
N	1,728	1,728	1,728	1,728
Kleibergen-Paap F	29.411	29.411	29.411	29.411

Note: Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1. Estimations are based on SIAB(1999-2014).

The last two columns of Table 4.7 show the results for different skill groups. While there is no significant effect on low-skilled natives, middle-skilled natives alter their relative task supply with increasing foreign share. This result is likely to be driven by the fact that middle-skilled workers have more suitable skills, which allow them to perform occupations

[12] The result is reported in column (3) of Table A4.1 in the appendix.

requiring more complex tasks, such as communication tasks, whereas the skill endowment of less-skilled workers constraint them in the labor market to perform more demanding tasks.

4.5 Conclusion

The labor market impact of immigration on natives is one of the mostly investigated topics in the labor and migration literature. However, our knowledge about the adjustment mechanisms of local labor markets is to date still limited. The effect of immigration highly depends on the degree of substitution between natives and immigrants. Contrary to studies which consider the substitutability with respect to education level, a recent strand of the literature investigates substitution with respect to workplace tasks workers perform. By considering the task requirements of occupations rather than the skill level of workers, the task-based approach introduces new scope of complementarities between natives and immigrants beyond the formal education.

Examining the substitution in tasks allows to relax the assumption that natives and immigrants with the same education level compete with each other. If immigrants and natives with the same formal education level possess different skills, they would perform different tasks and thus not compete for the same jobs. Following the task specialization hypothesis proposed by Peri and Sparber (2009), this paper investigates the change in natives' supply of communication tasks relative to manual tasks as a response to immigration in Germany. This adjustment mechanism could explain why empirical evidence shows no significant adverse effect of immigrants on the labor market outcomes of natives in Germany.

The results imply that natives increase their supply of communication tasks when the share of foreign workers increases. At the same time, they supply less manual tasks. This finding supports the hypothesis that immigrants and natives with the same skill level do not compete for the same jobs. These results are in line with previous evidence from other countries like the US and Spain. However, it should be kept in mind that due to differences in the construction of the task intensity measures, the size of the effect cannot be compared one-to-one with the evidence from other countries.

Overall, the findings indicate that natives and immigrants are not perfect substitutes in Germany. The evidence of task specialization helps us to understand why earlier studies found only negligible effect of immigration on natives' labor market outcomes in Germany.

The current paper showed that a major part of the overall task change arises from within occupation change rather than a between occupation change. The drawback of the previous studies for not accounting for the changing workplace requirements over time leads to an underestimation of the effect of immigration. Thus, the mechanisms behind changing task supply of natives in this paper and in earlier studies are different. While the evidence from the US and Spain is solely driven by occupational mobility, it has a small impact on the results of this paper. This is, however, not surprising as the occupational mobility is limited in Germany due to labor market rigidities. The current results mainly represent that task requirements of occupations changed substantially over the last decades and natives are affected by this change to a great extent.

A4 Appendix

Table A4.1: Robustness Analysis: IV Results

Independent Variable: Foreign share	(1)	(2)	(3)
Dependent Variable:			
$ln(C/M)$	0.951**	2.517*	5.354
	(0.469)	(1.309)	(6.797)
Year fixed effects	✓	✓	✓
Region fixed effects	✓	✓	✓
N	1,728	1,728	1,728
Kleibergen-Paap F	33.714	17.715	13.283

Note: Standard errors are clustered by labor market region. *** p<0.01; ** p<0.05; * p<0.1. Estimations are based on SIAB(1999-2014).

A4.1 Industry-Driven Task Demand

Region-specific industry-driven task demand index is generated as:

- Average communication and manual task contents among all workers in each industry, i, in year, t, and their corresponding ratio $(C/M)_{i,t}$ are calculated.
- Industry-level national employment growth since 1985, $g_{i,t}$ is calculated.
- By assuming that industries grew at their national growth rates in all regions, predicted employment share of industries within each region, r, and year, t, is estimated:

$$\widehat{emp}_{i,r,t} = \frac{Employment_{i,r,1985}(1+g_{i,t})}{\sum_{i=1}^{Ind} Employment_{i,r,1985}(1+g_{i,t})}$$

- Relative task demand of regions, $(C/M)_{r,t}^{Tech}$, is the average value of each industry's task intensity, $(C/M)_{i,t}$, weighted by the predicted employment shares:

$$\left(\frac{C}{M}\right)_{r,t}^{Tech} = \sum_{i=1}^{Ind} \widehat{emp}_{i,r,t} \left(\frac{C}{M}\right)_{i,t}$$

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Merve Çim – Curriculum Vitae

Professional Experience

2013–2018	RWI – Leibniz-Institute for Economic Research, Researcher, Research Department "Labor Markets, Education, Population".
2011	University of Mannheim, Teaching Assistant, Chair of Macroeconomics.

Education

2012–2018	PhD in Economics, Ruhr Graduate School in Economics – Ruhr University Bochum, Germany.
2009–2011	Master of Science in Economics, University of Mannheim, Germany.
2006	Semester abroad, Portuguese Catholic University, Porto, Portugal.
2005–2009	Bachelor of Science in Economics, Marmara University, Istanbul, Turkey.

Publications

- Bachmann, R., Cim, M. & Green, C. (2018). The Long-Run Effects of Labour Market Polarisation: Evidence from German Micro Data. *British Journal of Industrial Relations.*
- Cim, M., Kind, M. & Kleibrink, J. (2017). Occupational Mismatch of Immigrants in Europe: The Role of Education and Cognitive Skills. *Ruhr Economic Papers 687, RWI – Leibniz-Institute for Economic Research, Ruhr-University Bochum, TU Dortmund, University of Duisburg-Essen.*